Information Hostage: Inter-Firm Proprietary Information Sharing and Supply Chain Lock-In

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Abstract

I examine whether proprietary information sharing impacts supply chain lock-in, a state where the relationship continuation is driven less by ongoing efficiency and more by high exit costs. Using a hand-collected dataset of supply chain contracts, I develop a new measure of customer-to-supplier proprietary information sharing, based on the intensity of confidentiality provisions. Validation tests show that this measure correlates positively with customer firms' proprietary cost concerns, and that higher-confidentiality-intensity contracts are linked to improved suppliers' managerial learning in information environments, investment, and innovation. I find that supply chain relationships involving greater proprietary information sharing are more prone to lock-in, as reflected in a lower likelihood of termination following adverse supplier events (e.g., regulatory, competitive, or financial disruptions). These lock-in effects are more salient when customer firms face intense competition, rivals are highly innovative, or the focal relationship is the sole conduit for proprietary information exchange. To address endogeneity concerns, I leverage two plausibly exogenous shocks that alter the proprietary value of information already shared with suppliers, and find that decreases (increases) in proprietary value weaken (strengthen) supply chain lock-in, resulting in more (fewer) relationship terminations. Collectively, the findings highlight contracting frictions induced by proprietary inter-firm information exchange along the supply chain.

Keywords: inter-firm information sharing; proprietary information; supply chain; switching costs; innovation; real effects
JEL classification: D82, G14, G30, L14, M41
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1. Introduction

The smooth functioning of supply chains is critical for economic stability, as supply chains form an integral part of the economy and disruptions can cascade across industries, generating widespread adverse economic consequences (e.g., Hertzel et al., 2008; Costello, 2020; Attinasi et al., 2022). Both practitioners and academics have emphasized the role of information sharing in facilitating supply chain coordination and efficiency (e.g., Iakovou and White, 2022; McKinsey, 2022; Dai and Tang, 2024; Deloitte, 2024), as information asymmetry is a major contracting friction that hinders the efficient flow of goods and services across firms. Recent policy initiatives have also sought to encourage information sharing in supply chains, for instance, the 2016 Defend Trade Secrets Act (DTSA), which bolsters trade secret protection, and the 2022 Freight Logistics Optimization Works (FLOW) initiative, which enables participating firms to exchange logistics data. Despite the operational benefits and regulatory push, firms remain wary of the "dark side" of information sharing, including the risk of cyberattacks or losing control of shared knowledge (e.g., Cheung and Myers, 2008; Rundle, 2024). In this study, I investigate this "dark side" by examining whether proprietary information sharing with supply chain partners impacts the continuation of their relationship because of high costs of exit (i.e., supply chain lock-in).

Supply chain flexibility is critical in uncertain and volatile environments (Schönberger and Hald, 2024) and represents the key value driver of outsourcing under real options theory (e.g., Choi et al., 2018; Chenarides et al., 2021). Constraints on flexibility can restrict access to superior alternatives and heighten vulnerability when a partner's performance deteriorates (Williamson, 1996; Cohen and Agrawal, 1999; Peleg et al., 2002). Beyond its practical and regulatory relevance, my study extends the traditional view of information sharing, typically regarded as a mechanism

for mitigating contracting frictions and facilitating coordination, by highlighting its potential to generate switching costs and reduce structural flexibility in supply chains.

Conceptually, the effect of proprietary information sharing on supply chain lock-in is ex ante ambiguous. On one hand, firms have incentives to protect proprietary information disclosed to supply chain partners, yet their ability to do so diminishes once relationships end.[1] During the relationship, contractual safeguards, relational controls, and the threat of termination deter partners' opportunism (Klein, 1980; Stiglitz and Weiss, 1983). Once the relationship is terminated, however, these mechanisms vanish, as firms can no longer condition future business on compliance with information protection or rely on monitoring sustained by commercial dependency. While ex-post legal recourse such as trade secret litigation remains available, enforcement is costly and uncertain. Consequently, firms may prefer to maintain contractual ties with partners to whom they have disclosed sensitive information, since continued engagement preserves influence and monitoring capacity. This proprietary cost concern incentivizes firms to sustain relationships even when they become less productive, thereby fostering ex-post supply chain lock-in.

On the other hand, resource and power dependence theories posit that sharing proprietary knowledge can alter dependence structures and shift bargaining power (Emerson, 1962; Pfeffer and Salancik, 1978). Suppliers may leverage customers' proprietary information to strengthen their negotiation position, extracting higher margins at customers' expense (e.g., Kajüter and Kulmala, 2005; Drake and Haka, 2008; Windolph and Moeller, 2012). These shifts in bargaining dynamics can destabilize inter-firm relationships, increasing the risk of conflict, failure, and termination

[1] For instance, in July 2024, Tesla filed a federal lawsuit accusing its former supplier Matthews International of stealing trade secrets related to its battery manufacturing technology (https://ev.com/news/tesla-sues-ex-supplier-over-stolen-battery-trade-secrets-and-seeks-1b-compensation&blogId=3120, accessed 17 August 2025). In November 2020, Alien Technologies sued its former supplier Lynx Precision Products for patent infringement and trade secret misappropriation (https://insight.rpxcorp.com/litigation_documents/15050049?utm_source=chatgpt.com, accessed 18 August 2025).

(Inkpen and Beamish, 1997; Gulati and Sytch, 2007). Additionally, null effects are also plausible if firms prioritize other supply chain strategic considerations, such as the need for customized inputs (Barrot and Sauvagnat, 2016), adaptability (Lee, 2004), cost savings (Anderson and Dekker, 2009), or speed to market (Vesey, 1991), that outweigh proprietary cost concerns. Therefore, the net effect of information sharing on supply chain lock-in remains ex-ante ambiguous.

To investigate whether proprietary information sharing with supply chain partners impacts supply chain lock-in, I need a measure of potential proprietary information sharing, as actual information exchanges in supply chains are unobservable and no suitable measures exist. To proxy for this, I construct a measure based on the intensity of confidentiality provisions in supply chain contracts, which govern the protection of private information exchanged such as R&D, technical details, product design, and strategy. Proprietary cost concerns are a key consideration in supply chain contracting (e.g., Anton and Yao, 2002; Chen et al., 2022), and confidentiality provisions, among the most frequently disclosed clauses in supply chain contracts (e.g., Hui et al., 2025), serve as foundational governance tools to mitigate information leakage risk. To construct this measure, I collect all supply chain contracts filed with the SEC's EDGAR system since 2000, match contracting parties to Compustat firms, and extract key contractual features using a combination of the OpenAI API and manual inspection. The measure is defined as the number of words devoted to confidentiality provisions scaled by total contract length, providing a parsimonious yet informative proxy for proprietary information sharing. Using confidentiality provision intensity as a proxy for proprietary information sharing, I assume that the contractual emphasis on information protection reflects the anticipated magnitude and materiality of proprietary information exchange.

To validate my measure, I conduct a series of empirical tests. First, I document a marked increase in average confidentiality intensity after 2015, coinciding with the enactment of the DTSA,

which strengthened federal trade secret protection and plausibly encouraged inter-firm information sharing. Second, I examine contract-level determinants and find that customers with higher proprietary cost concerns, proxied by R&D intensity, patenting activity, and mentions of trade secrets in 10-Ks, tend to include more confidentiality provisions. Contracts between same-industry partners exhibit lower confidentiality intensity, consistent with reduced information sharing among potential product market rivals. Third, using a stacked difference-in-differences design, I find that suppliers entering higher-confidentiality-intensity contracts exhibit greater managerial learning in their information environment, investment, and innovation than those in lower-intensity contracts. While customers' proprietary information is shared primarily for coordination, it can also broaden suppliers' information sets and inform decision-making, given supply chain partners' economic interdependence (e.g., Houston et al., 2016; Cen et al., 2017). Thus, evidence of suppliers' greater learning in higher-intensity contracts supports construct validity, as learning should not systematically vary if confidentiality intensity were unrelated to the extent of information exchange. Collectively, these findings support the validity of confidentiality provision intensity as a proxy for customer-to-supplier proprietary information sharing.

Supply chain lock-in can manifest in reluctance to terminate ties when their ties become unproductive. Specifically, I examine whether proprietary information sharing constrains customer firms' flexibility to terminate supplier relationships when they become less advantageous, for example, following supplier disruptions. I construct a customer-supplier-year panel and use an indicator for relationship termination as the dependent variable. In the main analysis, I use supplier regulatory violations as a proxy for adverse events. The key regressor is the interaction between confidentiality provision intensity and the logarithm of suppliers' annual violation penalties. Consistent with expectations, I find that while supplier violations generally increase the likelihood

of termination, this effect is significantly attenuated in relationships with higher confidentiality intensity. These findings suggest that proprietary information sharing reduces termination flexibility in the face of adverse supplier events, thereby reinforcing supply chain lock-in.

To further strengthen these inferences, I examine two additional forms of supplier adversity: (i) heightened exposure to import competition and (ii) financial distress. Import competition captures external pressures that erode a supplier's competitiveness, while financial distress reflects financial vulnerabilities that raise the risk of production or delivery failures. In both settings, I find results consistent with the baseline: supply chain relationships with greater proprietary information sharing are significantly less likely to terminate following adverse supplier shocks. These findings reinforce the conclusion that information sharing contributes to supply chain lock-in by increasing firms' reluctance to sever ties even under unfavorable conditions.

There are two main endogeneity concerns in my study. First, because long-term supply chain relationships can yield benefits such as cost savings from routinized procedures (Myers, 2010), customers may voluntarily choose to remain with suppliers and share more proprietary information. Second, input specificity is a potential confounder, as customers relying on highly tailored inputs likely (i) share more proprietary information (e.g., product designs) with suppliers and (ii) face higher switching costs. To mitigate these concerns, besides explicitly controlling for input specificity in my baseline tests, I leverage two quasi-natural experiments that alter the proprietary value of information customers have already shared with suppliers, while leaving input specificity and other existing supply chain characteristics unaffected.

The first quasi-natural experiment is the adoption of the American Inventors Protection Act (AIPA). Effective November 29, 2000, the AIPA required U.S. patent applications to be disclosed 18 months after filing, regardless of whether the patents were ultimately granted or

rejected. Prior to the AIPA, applications were disclosed only upon grant. This reform substantially increased the baseline level of proprietary information released into the public domain, as patent applications often contain significant technical and strategic information (Hegde et al., 2018; Kim and Valentine, 2021). To the extent that such disclosures overlap with information already shared with suppliers,[2] the marginal proprietary value of that shared information declines, weakening customers' incentive to maintain relationships solely for safeguarding purposes. I therefore predict that customers more affected by the AIPA should become less subject to information sharing-induced lock-in and more likely to terminate supplier relationships. Consistent with this prediction, I find that affected customers increase relationship terminations following the AIPA.

I next exploit a reverse quasi-natural experiment, the enactment of the Leahy-Smith America Invents Act (AIA), which reduced public R&D disclosure and thereby increased the proprietary value of information shared with suppliers. The AIA shifted the U.S. patent system from first-to-invent, under which patent rights went to the "first and true" inventor even if competitors filed similar applications earlier, to first-to-file, where patent rights depend strictly on filing date. Effective for patent applications filed on or after March 16, 2013, this change made early disclosure of intellectual property riskier, as any revelation prior to filing could allow competitors to preempt the firm's applications and permanently block rights. Thus, this shift raised the costs of public R&D disclosure, leading innovation-intensive firms to reduce R&D disclosure to better safeguard intellectual property (Huang et al., 2021). By lowering baseline R&D disclosure, the AIA heightened the marginal proprietary value of information shared with suppliers, strengthening customers' incentives to preserve these relationships to protect information. I therefore predict that customers more affected by the AIA become more susceptible to information

[2] This assumption is reasonable given the coordinated innovation between supply chain partners (Cao et al., 2024) and that R&D information is the most frequently referenced category of shared information in supply chain contracts.

sharing-induced lock-in and thus less likely to terminate supplier relationships. Difference-in-differences analyses confirm this prediction. Taken together, the AIPA and AIA experiments provide causal evidence that proprietary information sharing contributes to supply chain lock-in.

To further strengthen the inference that customer firms' proprietary cost concerns drive supply chain lock-in, I conduct a series of cross-sectional tests. First, I expect lock-in effects to be more pronounced when customers operate in highly competitive product markets, where incentives to safeguard sensitive information are stronger. Second, I predict stronger effects when customers' rivals are more innovative, as such rivals are better positioned to exploit leaked information. Third, I expect greater lock-in when the focal relationship is the sole conduit for proprietary information exchange, i.e., when no other inter-firm ties exist, such as common institutional ownership or board members. The results align with my predictions, reinforcing the mechanism that customers' proprietary cost concerns contribute to supply chain lock-in.

My study contributes to the literature in three primary ways. First, I extend research on the economic consequences of information sharing in supply chains, by showing that proprietary information sharing can generate contracting frictions, specifically supply chain lock-in. The traditional view in economics, finance, and operations management, grounded in analytical and case studies, emphasizes the benefits of information sharing in mitigating supply chain frictions and enhancing coordination such as lower inventory holding costs (Cachon and Fisher, 2000; Sahin and Robinson, 2005) and reduced bullwhip effects (where small demand fluctuations are amplified along the supply chain). In accounting, two recent working papers study customer firms' sharing of demand forecasts with suppliers: Bushee et al. (2024b) show that such sharing reduces suppliers' reliance on customers' public disclosures, while Pandey (2024) finds it reduces suppliers' learning from stock prices by lowering price informativeness. My study highlights that customer-

to-supplier proprietary information sharing raises switching costs and constrains supply chain flexibility. Unlike transitory demand forecasts, the R&D-related information I primarily study is longer-lived and more consequential, locking customers into existing relationships.

Second, my findings add to the broader literature on the economic consequences of inter-firm information flows. Prior research shows that corporate decisions are shaped by information transmitted through various inter-organizational channels including competitors (Bernard et al., 2020; Bushee et al., 2024a), strategic alliances (Kepler, 2021), and FOIA requests (Glaeser et al., 2023). Within the supply chain context, prior studies document that public disclosures (e.g., management forecasts; Radhakrishnan et al., 2014; Chiu et al., 2022) and private channels (e.g., demand forecasts; Bushee et al., 2024b; Pandey, 2024; or common institutional investors; Freeman, 2025) facilitate supplier learning. I extend this literature by showing that proprietary information sharing increases relationship stickiness and switching costs, thereby constraining firm flexibility. This finding also connects to the financial contracting literature, where analytical models predict that informed lenders accumulate proprietary borrower information to lock in clients and extract rents, thus reducing borrower flexibility (Sharpe, 1990; Rajan, 1992).

Third, I introduce a contract-based measure of proprietary information sharing in supply chains, captured by the intensity of confidentiality provisions in supply chain agreements. These provisions govern the information protection, and their prominence likely reflects contracting parties' ex-ante expectations about the volume and materiality of information exchanged. Unlike prior work focused on narrower forms such as demand forecasts and production capacity, I consider a broader scope of proprietary information including R&D, product specifications, trade secrets, and strategic plans (see Appendix B for examples). My measure may serve as a useful tool for future research on proprietary information flows in inter-firm relationships more broadly.

2. Background, Related Literature, and Hypothesis Development

2.1 Peer Information Flows in Inter-Firm Relationships

The accounting literature on peer information flows has traditionally examined how firms make their decisions by incorporating peer firms' public information, such as earnings announcements, financial reports, restatements, conference calls, and observable investments, into their own decisions. For example, Beatty et al. (2013) and Li (2016) show that financial misreporting distorts peer investment decisions. Cho and Muslu (2021) find that firms increase capital investment and inventory when peers' MD&A narratives become more optimistic. Truong (2023) documents that firms accelerate their own earnings announcements in response to peers' early earnings announcements. Bustamante and Fresard (2021) document that firms' investment responds positively to the investment of product market peers.

A growing body of work examines how private information flows across firms influence decision-making. This research explores private information transmitted in various inter-firm settings, including competitors, strategic alliances, and M&As. For instance, Bushee et al. (2024a) find that private communication among competitors enhances the informativeness of management forecasts, and Kepler (2021) shows that private communication in strategic alliances can substitute for public disclosures. Bourveau et al. (2020), Bertomeu et al. (2021), and Pawliczek et al. (2022) argue that voluntary disclosures can serve as a channel for tacit collusion and coordination. In the M&A context, Afrin (2022) demonstrates that private information acquisition during due diligence improves bidders' investment efficiency and innovation. Together, these studies underscore the importance of inter-firm private information sharing in shaping corporate decision-making. However, while prior research has focused primarily on horizontal or competitive relationships, vertical supply chain relationships remain an economically significant but underexplored setting.

2.2 Private Information Sharing in Supply Chain Relationships

In supply chains, private information sharing is not only routine but often essential for coordination and efficiency. While prior research has primarily focused on customers' disclosure of product demand forecasts to suppliers (e.g., Mishra et al., 2009; Cui et al., 2015; Brüggen et al., 2021; Bushee et al., 2024b; Pandey, 2024), information exchanges in supply chains encompass a much broader set of proprietary content. These include R&D-related information (e.g., R&D, patents, clinical trials), product information (e.g., designs, formulations, pricing), forward-looking strategic content (e.g., tactical plans, marketing strategies, business plans), regulatory documentation (e.g., licenses, permits), and financial information (e.g., budget, financial condition). Reflecting the proprietary and sensitive nature of these exchanges, supply chain contracts, as illustrated in Appendix B, frequently include bilateral confidentiality provisions designed to safeguard shared information.[3]

Prior analytical models and case studies in industrial organization and operations management emphasize the operational benefits of information sharing in supply chains, particularly around customer demand forecasts. Such sharing has been shown to reduce inventory holding costs (Cachon and Fisher, 2000; Sahin and Robinson, 2005) and mitigate the bullwhip effect. Recent evidence in accounting highlights similar effects: Bushee et al. (2024b) show that customer demand forecasts reduce the spillover of optimistic bias from customer to supplier management forecasts, while Pandey (2024) finds that such forecasts crowd out informed traders and reduce suppliers' learning from stock prices.

[3] A foundational element of proving the existence of a trade secret and trade secret misappropriation under the Defend Trade Secrets Act or state law, or at the U.S. International Trade Commission, is whether the claimant has taken reasonable measures to maintain the secrecy of the trade secret (see 18 U.S.C. §§1836-39). Confidentiality provisions in contracts are critical as evidence of reasonable measures to maintain secrecy, and thus the existence of a protected trade secret (e.g., Frederick et al., 2024).

At the same time, the proprietary nature of shared information exposes firms to risks, including partners' opportunistic behavior or leakage. Counterparties may use shared information to gain bargaining power and erode the margin of the focal firm during contract negotiations (e.g., Kajüter and Kulmala, 2005; Windolph and Moeller, 2012). The American Society for Industrial Security (ASIS) 2002 survey identifies suppliers as among the leading sources of proprietary information loss for customers (Boni et al., 2002). Suppliers' access to customer trade secrets and other sensitive information can undermine customers' competitive advantage if leaked to rivals (e.g., Hughes and Kao, 2001; Chen et al., 2022; Kang et al., 2022; Afrin et al., 2025). In this study, I examine the *dark side* of proprietary information sharing in supply chains through two key innovations. First, I develop a new, contract-based measure of information-sharing intensity, based on the prominence of confidentiality provisions, which captures a broad range of proprietary exchanges beyond commonly studied demand forecasts. Second, I investigate whether proprietary information sharing creates supply chain lock-in, constraining customers' flexibility to exit relationships even after they become less advantageous.

2.3 Supply Chain Switching Costs and Lock-In

In supply chains, switching costs refer to the costs a firm incurs when replacing an existing trading partner, and these costs can take many forms (Williamson, 1985). Firms may face search and evaluation costs when identifying new suppliers (Bernard et al., 2019), technical integration and reconfiguration costs when aligning processes and systems (Handfield and Nichols, 2002), or the loss of accumulated know-how and routines built through repeated interactions (Dyer and Singh, 1998). Such costs are a central parameter of sourcing decisions, evidenced by more recent studies (Antràs et al., 2017; Bernard et al., 2019).

When switching costs are high, firms may experience supply chain lock-in, a state in which relationship continuation is driven less by ongoing efficiency and more by the high costs of exit. Although lock-in can sometimes be beneficial by encouraging cooperation and joint value creation, it also constrains flexibility, limits access to superior alternatives, and increases vulnerability when a partner's performance deteriorates (Williamson, 1996; Cohen and Agrawal, 1999; Peleg et al., 2002). Flexibility, however, is the key value driver of outsourcing under real options theory (e.g., Choi et al., 2018; Chenarides et al., 2021). Supply chain lock-in may manifest in longer-than-optimal relationship durations, reluctance to terminate under adverse events, and reduced responsiveness to changing market or technological conditions. Recent empirical studies provide supportive evidence on the supply chain lock-in when suppliers provide specific inputs or customers face high search efforts (Barrot and Sauvagnat, 2016; Bernard et al., 2019; Inoue and Todo, 2019). Further, supply chain lock-in amplifies the propagation of suppliers' shocks to customers (Barrot and Sauvagnat, 2016).

This study focuses on a distinct and unexplored mechanism: the role of proprietary information sharing in inducing supply chain lock-in. The risk that proprietary information may be misused or leaked makes terminating relationships more costly, increasing the likelihood of continuation even when ties become unproductive (e.g., after supplier disruptions). By developing a novel contract-based measure of potential proprietary information sharing, linking this measure to subsequent patterns of relationship persistence and termination, and exploiting quasi-natural experiments that shift the proprietary value of already-shared information, I isolate an information sharing-based mechanism of supply chain lock-in. In doing so, my study also extends the switching cost literature into the domains of inter-firm information flows.

2.4 Hypothesis Development

While information sharing with supply chain partners is often viewed as a mechanism for enhancing coordination and operational efficiency (e.g., Cachon and Fisher, 2000; Sahin and Robinson, 2005), it is not without costs. A key concern is the risk of information leakage and misappropriation, particularly when the shared information is strategically valuable (Baiman and Rajan, 2002). Proprietary information shared with supply chain partners, such as technical know-how, R&D details, and product strategies, may be inadvertently or deliberately leaked to competitors, undermining focal firms' competitive positions.

Firms have incentives to protect proprietary information shared with supply chain partners, but their ability to do so weakens substantially once the relationship ends. During the relationship, ex-ante governance mechanisms (e.g., contractual safeguards) and ongoing relational controls (e.g., monitoring and dependence on continued business) help deter counterparties' opportunistic behavior. The threat of termination itself also disciplines partners by reducing incentives to misuse proprietary information (Klein, 1980; Stiglitz and Weiss, 1983). However, once the relationship is terminated, these governance mechanisms give way to ex-post enforcement. The focal firm loses formal contractual safeguards and operational oversight, for example, it can no longer condition future business on compliance with information protection or leverage routine interactions for monitoring. Although ex-post legal recourse, such as trade secret litigation, remains available, enforcement is costly and uncertain without ongoing access to partners' operations. In practice, firms have to rely on imperfect signals such as market intelligence, reverse engineering, or whistleblowers, which often provide incomplete or contested evidence of misappropriation.

Thus, I argue that due to proprietary cost concerns and the increased difficulties in protecting proprietary information post-termination, focal firms are reluctant to sever ties with supply chain partners to whom they have disclosed sensitive information. By maintaining ongoing

contractual supply chain relationships, focal firms can preserve influence and monitoring capacity. In this way, the desire to protect proprietary information creates an incentive to sustain supply chain relationships, even when they become less advantageous, thereby fostering ex-post lock-in. I formalize the main hypothesis of this study as follows:

H: *Proprietary information sharing with supply chain partners leads to supply chain lock-in, specifically, reduces focal firms' incentive to terminate relationships with supply chain partners, even when those relationships become less advantageous.*

Nevertheless, there are countervailing forces that suggest the opposite possibility, i.e., greater proprietary information sharing can reduce, rather than amplify, supply chain lock-in. Resource dependence theory (Pfeffer and Salancik, 1978) and power dependence theory (Emerson, 1962) posit that sharing proprietary knowledge can alter dependence structures and shift bargaining power. Suppliers may exploit acquired information to strengthen their position in contract negotiations, extracting higher margins at the focal firm's expense (e.g., Kajüter and Kulmala, 2005; Drake and Haka, 2008; Windolph and Moeller, 2012). Such shifts in power due to knowledge acquisition can destabilize inter-firm partnerships (Inkpen and Beamish, 1997), making relationships more prone to conflict, failure, or termination (e.g., Gulati and Sytch, 2007). In addition, null effects are also plausible if firms prioritize other strategic considerations over proprietary cost concerns in supply chain management decisions. The need to source highly customized inputs (Barrot and Sauvagnat, 2016), maintain adaptability (Lee, 2004), achieve cost savings (Anderson and Dekker, 2009), or speed products to market (Vesey, 1991) may outweigh the incentives of safeguarding information. Therefore, it remains ex-ante ambiguous whether proprietary information sharing with supply chain partners affects supply chain lock-in.

3. Sample, Data, and Research Design

3.1 Sample Construction

I compile a sample of material supply chain contracts filed through the SEC's EDGAR system over the years 2000-2024. Under Item 601(b)(10) of Regulation S-K, U.S. public firms are required to disclose material business contracts as exhibits in their SEC filings (i.e., one exhibit corresponding to one material contract). Following established methodologies (Costello, 2013; Hui et al., 2025), I start by identifying all material supply chain contracts using the WRDS SEC Analytics Suite, which provides the filing name and description for each exhibit.[4] I then web scrape the full text of these contracts from EDGAR. For filings in PDF or image-based formats, I apply Optical Character Recognition (OCR) to extract textual content. After obtaining contract text, I manually review the first page of each contract to further exclude non-supply chain and duplicated contracts. I use the OpenAI API to extract key contractual features, including the supplier and customer names, contract entering date, duration, and confidentiality provisions, and conduct spot checks to verify extraction accuracy.[5] I restrict the sample to bilateral contracts, i.e., contracts with one supplier and one customer. To link the contracting parties to Compustat, I perform fuzzy name matching with manual inspection and manually match all remaining unmatched firms. Subsidiaries are matched to their public parent firms at the time of contract initiation. I exclude contracts if neither party can be linked to a public firm in Compustat, if either firm operates in the financial sector, or if neither firm has available total assets data. The resulting sample comprises 4,103 supply chain contracts with entering dates in 1999-2024, representing 848 unique public supplier firms and 1,139 unique public customer firms. Table 1 summarizes the sample selection procedure.

[4] To isolate exhibits that are likely to be supply chain contracts, I retain material contracts whose filing names or descriptions contain at least one of the following keywords: "Supply," "Supplie*," "Manufactur*," "Vendor," "OEM," "Product," "Procure," or "Goods." I further refine the sample by excluding non-supply chain contracts, identified based on the presence of terms such as: "Revis*," "Amend," "Modif*," "Restate," "Supplement," "Addendum," "Memorandum," "Letter," "Warranty," "Terminate," "Dismiss," "Settle," "Discontinue," "Suspend," "Cessation," "Lease," "Stock," "Equity," "Security," "Loan," "Credit," "Employ," "Mortgage," "Escrow," and "Incentive."
[5] I use GPT-4o mini with temperature 0.

[Insert Table 1 Here]

3.2 Measurement of Proprietary Information Sharing

Supply chain relationships often involve the exchange of proprietary information, leaving proprietary cost concerns as a key consideration in supply chain contracting (e.g., Anton and Yao, 2002; Chen et al., 2022; Kang et al., 2022). To mitigate these risks, firms often rely on confidentiality provisions as foundational and formal governance mechanisms, which are among the most frequently disclosed clauses in supply chain contracts (e.g., Hui et al., 2025). Such provisions formally govern how sensitive information, such as trade secrets, technical data, and other confidential materials, is exchanged and safeguarded. Confidentiality clauses typically specify the parties involved, the categories of protected information, and the scope of obligations, thereby ensuring that shared knowledge is not disclosed to or misused by unauthorized parties (Leibman and Jones, 2020).

Most confidentiality provisions in supply chain contracts are bilateral, requiring both parties to protect exchanged information (see Examples 1-4 in Appendix B). In occasional instances, clauses are unilateral, where only one party discloses sensitive information and the counterparty agrees to maintain confidentiality (see Examples 5-6 in Appendix B). The scope of these provisions often extends beyond explicitly shared information to encompass derivative insights or knowledge gained from that information, protecting against both direct and indirect risks of leakage. In this way, confidentiality clauses play a central role in facilitating private information sharing while managing associated proprietary risks in inter-firm relationships.

Legal and economics theories of contract design emphasize that contracts are inherently incomplete due to limits on enforceability, transaction costs, and bounded rationality (e.g., Hart and Moore, 1988; Tirole, 1999; Scott, 2006). The incompleteness of contracts impose constraints

on how much can be contractually specified, as adding more provisions increases negotiation and enforcement costs and can reduce contractual flexibility (Scott and Triantis, 2005). Thus, firms face trade-offs when allocating contractual space. I therefore assume that the relative prominence of confidentiality provisions as an ex-ante choice: the greater the anticipated exchange of material proprietary information, the stronger the contractual emphasis on confidentiality safeguards.

Building on this intuition, I develop a contract-based measure of proprietary information sharing in supply chains (*Conf Word Ratio*). This measure is defined as the number of words contained in confidentiality-related provisions, scaled by the total word count of the contract. It captures the contractual emphasis placed on protecting sensitive information and, by extension, the anticipated intensity of proprietary information exchange between suppliers and customers. To construct the measure, I identify confidentiality-related sections using a combination of automated extraction with the OpenAI API and manual verification, and then compute the ratio of those sections' word counts to the full contract length.

3.3 Summary Statistics

I begin with summary statistics to provide context for the nature of confidentiality provisions in supply chain contracts. Figure 1 presents a word cloud generated from confidentiality-related sections in my sample. The four most frequently occurring terms are *information*, *confidential*, *disclose*, and *party*. Other prominent terms, such as *proprietary*, *product*, and *business*, also highlight related proprietary information exchanged in supply chains.

[Insert Figure 1 Here]

To better understand the types of information potentially shared, I manually review a random subsample of 100 contracts from my main sample and develop a keyword list corresponding to several categories of proprietary information disclosed in confidentiality

provisions. Figure 2 reports the distribution of these categories in the main sample. In 44% of contracts, confidentiality provisions refer only to generic terms, such as "trade secrets," "proprietary information," "private information", or "confidential information", without specifying the information type. The remaining 56% explicitly define the scope of protected information, spanning several categories. 47% of contracts mention R&D-related information, such as patents, intellectual property, manufacturing technologies, and test data. Other frequently cited categories include business strategy (16%; e.g., business or marketing plans), regulatory compliance (17%; e.g., regulatory documentation or international registration), product (14%; e.g., demand, pricing, or formulation), and financial information (13%; e.g., budgets or financial conditions). References to personnel or consumer data are relatively rare.

[Insert Figure 2 Here]

Table 2 Panel A reports descriptive statistics for key contract- and firm-level characteristics. The mean value of *Conf Word Ratio* is 0.035, indicating that, on average, 3.5% of words in a supply chain contract pertain to confidentiality provisions. The average contract duration is 4.9 years, with a median of 5.0 years, consistent with prior research (Costello, 2013).[6] Approximately 34.4% of contracts have a duration shorter than five years, comparable to the 33.2% reported by Bushee et al. (2024b). In addition, 57.3% of contracts include an automatic renewal clause, under which the contract is continuously extended until either party chooses to terminate it. Panel B reports the public listing status of the contracting parties. Of the 4,103 contracts in my sample, 34.1% (~1,399 contracts) involve both parties being publicly listed firms existing in Compustat, while the remaining contracts involve only one publicly listed party.

[Insert Table 2 Here]

[6] The mean value of my sample is somewhat lower than that of Costello (2013), because my sample also includes short-term contracts (i.e., with duration shorter than a year).

Figure 3 presents the time trend in average confidentiality provision intensity, measured by the average *Conf Word Ratio* by contract start year between 1999 and 2024. Confidentiality intensity remains relatively stable from 1999 to 2014 at approximately 3-4% but rises notably after 2015. This increase is potentially related to the passage of the DTSA, which strengthened trade secret protection at the federal level. Introduced in the Senate in July 2015 and signed into law in May 2016, the DTSA expanded enforcement by allowing trade secret owners to pursue civil actions in federal court and seek remedies that were previously unavailable.[7]

[Insert Figure 3 Here]

Table 2 Panel C reports the industry distribution of contracts based on the Fama-French 48 industry classification of the customer firm, along with the average confidentiality intensity by industry. The distribution is skewed toward pharmaceutical industry, which accounts for 20.3% of contracts. Table 2 Panel D tabulates the analogous industry distribution based on the supplier firm, with pharmaceutical firms representing 15.0% of contracts.

3.4 Determinants of Confidentiality Provision Intensity

Because actual proprietary information sharing within supply chains is unobservable to outsiders, I conduct a series of tests to assess whether confidentiality provision intensity plausibly captures the extent of potential proprietary information exchange between suppliers and customers. As a starting point, I examine its determinants. Specifically, I regress the continuous measure of confidentiality provision intensity on supplier and customer firm characteristics including R&D

[7] Before the DTSA, trade secret law was governed by state-level statutes (Uniform Trade Secrets Act variants), and the protection varied in strength and enforceability. The DTSA established uniform and stronger federal protection, especially benefiting firms in states with weaker pre-existing laws and firms operating across state and national borders (e.g., Quick et al., 2016). Under the DTSA, for "information" to qualify as a trade secret, the owner must have "taken *reasonable measures* to keep [the] information secret" (18 U.S.C. §1839(3)). Confidentiality provisions in contracts are critical as evidence of reasonable measures to maintain secrecy, and thus the existence of a trade secret (e.g., Frederick et al., 2024). Consequently, firms may include more confidentiality provisions following the DTSA.

intensity, trade secret reliance, innovation activity, firm size, profitability, and financial leverage, as well as other contract-level features.

Table 3 presents the results. The sample size shrinks to 1,249 because the analysis is restricted to contracts where both supplier and customer firms are publicly listed and have non-missing control variables. Columns 1-2, 3-4, and 5-6 examine R&D intensity, trade secret reliance, and innovation activity, respectively, as the primary explanatory variables, while columns 7-8 pool all three measures. All columns include year fixed effects, and columns 2, 4, 6, and 8 additionally include supplier and customer industry fixed effects. I find significant positive associations between confidentiality provision intensity and customer firms' R&D intensity, trade secret reliance, and innovation activity, while the supplier-side results are generally weak and sensitive to specification choices. These results suggest that firms, particularly customer firms, with greater proprietary information concerns tend to adopt more intensive confidentiality provisions.

[Insert Table 3 Here]

I also find that contracts between firms in the same industry exhibit lower confidentiality intensity, consistent with the notion that firms are less willing to share sensitive information with potential competitors. In addition, contracts that include automatic renewal clauses are associated with higher confidentiality intensity, potentially reflecting greater trust between parties, as automatic renewals are more common in relationships characterized by continuity and mutual confidence (e.g., Keith et al., 2016). Taken together, these results suggest that confidentiality provision intensity is systematically related to the underlying potential for proprietary information sharing in supply chain relationships, particularly customer-to-supplier proprietary information sharing, thereby lending support to its validity as a proxy.

In addition, I examine whether suppliers entering into higher-confidentiality-intensity contracts exhibit greater managerial learning than those in lower-intensity contracts. Although customers' proprietary information is shared primarily for supply chain coordination, it can also expand suppliers' information sets and inform decision-making, given supply chain partners' economic interdependence (e.g., Houston et al., 2016; Cen et al., 2017). Thus, evidence of suppliers' greater managerial learning in higher-confidentiality-intensity contracts supports construct validity, as learning should not systematically differ if confidentiality intensity were unrelated to the magnitude and materiality of information exchange. I focus on three dimensions of suppliers' managerial learning: (i) information environment quality, (ii) investment quality, and (iii) innovation quality, given that a substantial portion of contracts involve R&D-related information sharing. This stacked difference-in-differences analysis is described in detail in Online Appendix Section OA.1. The results support the construct validity of my measure of customer-to-supplier proprietary information sharing

4. Baseline Analyses

4.1 Proprietary Information Sharing and Supply Chain Relationship Termination: Suppliers' Regulatory Violations

Supply chain lock-in can manifest in firms' reluctance to terminate supply chain relationships after their relationships become unproductive.[8] Specifically, I examine whether customer-to-supplier proprietary information sharing constrains customer firms' flexibility to terminate supplier relationships when they become less advantageous, for example, when suppliers

[8] Supply chain lock-in can also manifest in longer-than-optimal relationship durations, but it is empirically challenging to measure the optimal duration. In Online Appendix Table OA4, I document a positive association between confidentiality provision intensity and ex-post relationship duration, consistent with lock-in effects. However, these results should be interpreted with caution, as longer relationships are not inherently negative and may instead reflect stability and cooperation.

experience adverse events. I construct a customer-supplier-year panel from years 1999 to 2024 and estimate the following ordinary least squares (OLS) model:

$$\begin{aligned} Termination_{i,j,t} \quad & (1) \\ &= \beta_0 + \beta_1 Conf\ Word\ Ratio_{i,j,t} \times Supplier\ Violation_{i,j,t} \\ &+ \beta_2 Conf\ Word\ Ratio_{i,j,t} + \beta_3 Supplier\ Violation_{i,j,t} + \sum \beta_i\ Controls_{i,j,t} \\ &+ FEs + \varepsilon_{i,j,t} \end{aligned}$$

where *i* indexes customer firms, *j* supplier firms, and *t* fiscal years. The dependent variable, *Termination*, is an indicator equal to one if the supply chain relationship gets terminated in the year *t*. I use supplier regulatory violations (*Supplier Violation*) as the proxy for adverse events, measured as the natural log of one plus the supplier's regulatory penalties in year *t*.[9] The key independent variable is the interaction between confidentiality provision intensity (*Conf Word Ratio*) and *Supplier Violation*. I control for a set of customer characteristics, including R&D intensity (*R&D*), firm size (*Size*), firm age (*Age*), financial leverage (*Lev*), return on assets (*ROA*), loss occurrence (*Loss*), and cash holdings (*Cash*). I include industry pair × year fixed effects to control for industry pair-level time-variant factors. In alternative specifications, I further include (i) customer and supplier firm fixed effects to absorb time-invariant firm-specific characteristics, and (ii) customer-supplier pair fixed effects to control for time-invariant firm pair-specific factors. Standard errors are clustered at the two-digit SIC customer industry level to account for the within-industry correlation of residuals across firms and years.

I tabulate the descriptive statistics in Table 4 Panel A and the results of estimating Eq. (1) in Panel B with various fixed effect structures. Specifically, columns 1-2 include industry pair ×

[9] In Online Appendix Table OA5 Panel A, my inferences are consistent when using suppliers' regulatory violation penalties scaled by total assets (*Supplier Violation Alt*) as an alternative measure of suppliers' regulatory violations.

year fixed effects, columns 3-4 include industry pair × year, customer firm, and supplier firm fixed effects, and column 5-6 include industry pair × year and firm pair fixed effects. Across all specifications, the coefficients on *Supplier Violation* are significantly positive, indicating that, on average, supplier regulatory violations increase the likelihood of relationship termination. More importantly, the interaction terms, *Conf Word Ratio* × *Supplier Violation*, are consistently significantly negative, showing that this effect is attenuated in relationships characterized by higher confidentiality provision intensity, i.e., greater proprietary information sharing. These findings support the prediction that proprietary information sharing reduces termination flexibility in the face of adverse supplier events, thereby reinforcing supply chain lock-in.

[Insert Table 4 Here]

4.2 Proprietary Information Sharing and Supply Chain Relationship Termination: Suppliers' Alternative Adverse Events

To strengthen the inferences, I examine two additional forms of supplier adversity: (i) heightened exposure to import competition and (ii) financial distress. Import competition captures external pressures that erode a supplier's competitiveness, while financial distress heightens the risk of production and supply failure. In both settings, I estimate specifications analogous to those in Section 4.1. To measure suppliers' exposure to import competition, I use large import tariff reductions as plausibly exogenous shocks that trigger significant increases in competition faced by U.S. product market incumbents (e.g., Fresard, 2010; Huang et al., 2017). To measure suppliers' financial distress, I compute the firm-level probability of default using the Merton (1974) model, which treats equity as a call option on firm assets and derives default likelihood from capital structure and asset volatility (Merton, 1974; Bharath and Shumway, 2008). I classify supplier firm-years with default probabilities exceeding 10% as financially distressed (*Supplier Fin Distress* =

1) (Phillips and Sertsios, 2013).[10] The results in Table 5 parallel those based on regulatory violations. Specifically, although suppliers' increased import competition and financial distress both raise the likelihood of relationship termination on average, this effect is significantly attenuated when contracts exhibit greater confidentiality provision intensity. Put differently, supply chain relationships characterized by greater proprietary information sharing are less likely to be severed, even when suppliers face these adverse shocks.

[Insert Table 5 Here]

Taken together, the evidence in Tables 4-5 suggests that customer-to-supplier proprietary information sharing constrains customers' exit flexibility under suppliers' adverse circumstances. By lowering termination likelihood in the presence of suppliers' regulatory, competitive, or financial disruptions, proprietary information sharing reinforces supply chain lock-in. These findings highlight that the persistence of supply chain relationships is not merely a reflection of stability or cooperation, but also of constraints arising from proprietary information sharing, which increase customers' reluctance to sever ties under unfavorable supplier conditions.

4.3 Proprietary Information Sharing and Supply Chain Relationship Termination: Robustness Tests of Baseline Findings

To ensure the robustness of my baseline findings, I conduct a battery set of additional tests. In Table 6 Panel A, I replace the continuous measure of confidentiality provision intensity with its decile rank (*Conf Word Decile*). Panel B incorporates more stringent fixed effects specifications, including contract fixed effects (Columns 1-2) and contract plus state-pair × year fixed effects (Columns 3-4). Panel C addresses concerns that the results may be driven by input specificity or supplier importance by directly controlling for these factors and their interactions with

[10] In Online Appendix Table OA5 Panel B, my inferences are consistent when using Ohlson's O-score (*Supplier Fin Distress Alt*) as an alternative measure of suppliers' financial distress.

confidentiality provision intensity. Specifically, I define input specificity as the total number of words in the "Product Specifications" section of the contract (Costello, 2013) (*Input Specificity*). I define supplier importance as an indicator variable equal to one if it is the customer firm that files the contract (*Material Supplier*). Last, to mitigate concerns about COVID-19-related disruptions, I exclude all supply chain relationships initiated or terminated during the pandemic period (see Table 6 Panel D). Across all these tests, the main inferences remain robust.

[Insert Table 6 Here]

5. Quasi-Natural Experiments

5.1 American Inventors Protection Act Mandatory Patent Disclosure

There are two main endogeneity concerns in my study. First, because stable and long-term supply chain relationships can generate benefits such as cost savings from routinized procedures (Myers, 2010), customer firms may voluntarily choose to remain locked into suppliers and share more proprietary information. Second, input specificity could confound the results: when inputs are highly customized, customer firms are more likely to (i) share proprietary information (e.g., product designs) with suppliers and (ii) face higher switching costs if replacement becomes needed. To address these concerns, I exploit two quasi-natural experiments that plausibly affect only the proprietary value of information already shared with suppliers, without altering input specificity or other existing supply chain characteristics.

The first quasi-natural experiment I examine is the adoption of the American Inventors Protection Act (AIPA). Effective November 29, 2000, the AIPA aims to improve the timeliness and expand the scope of patent disclosures to the public domain by mandating the disclosure of U.S. patent applications 18 months after their filing, irrespective of whether the patents are ultimately granted or rejected. Before the AIPA, patent applications were disclosed only upon

patent grant. This shift introduced considerable proprietary costs for disclosing firms, as these applications often contain significant technical and strategic information (Hegde et al., 2018; Kim and Valentine, 2021; Glaeser and Lang, 2024). By increasing the baseline level of proprietary disclosure to the public (e.g., competitors), the AIPA reduced the marginal proprietary value of information previously shared with suppliers. Consequently, customer firms became less concerned about protecting already-disclosed information through ongoing supply chain relationships, altering the cost-benefit calculus of maintaining such ties. I therefore conjecture that customer firms affected by the AIPA become less subject to proprietary information sharing-induced lock-in and, as a result, are more likely to terminate supplier relationships after the AIPA relative to unaffected customer firms.

Following Kim and Valentine (2021), I measure a firm's relative information spill-outs based on its own and its NAICS four-digit peers' patenting activities and the time lag between patent filing and patent disclosure prior to the AIPA. Firms with longer filing-to-publication lags were more exposed to the AIPA shock, as the reform forced them to accelerate disclosure. I define treatment customer firms ($Treat_{AIPA} = 1$) as those in the top three deciles of information spill-outs. Treatment customer firms' patent information spills over to their industry peers following the AIPA, revealing more proprietary information to the public. Control firms ($Treat_{AIPA} = 0$) are remaining customer firms. I test the effects of the AIPA on supply chain termination using a difference-in-differences design. The pre-event period is 1995-1999 ($AIPA = 0$) and the post-event period is 2001-2005 ($AIPA = 1$). I exclude the year 2000 for cleaner identification. The dependent variable, *Termination Num*, is the natural log of one plus the number of supplier relationship terminations for a customer firm in a given year. The key independent variable is the interaction term, $Treat_{AIPA} \times AIPA$. I include firm fixed effects to absorb time-invariant firm characteristics,

and year fixed effects to absorb time-varying factors. In alternative specifications, I further include industry × year fixed effects to absorb industry-level time-varying factors. The standalone $Treat_{AIPA}$ variable is subsumed by firm fixed effects and *AIPA* is subsumed by year fixed effects.

As reported in Table 7 Panel A, the interaction term, $Treat_{AIPA} \times AIPA$, consistently loads positively and significantly across all columns. The dynamic effects presented in Figure 4 Panel A support the parallel trends assumption. These results indicate that following the AIPA, affected customer firms, those forced to accelerate disclosure of patent information, terminate more supplier relationships relative to unaffected firms. This evidence is consistent with the interpretation that proprietary information sharing contributes to supply chain lock-in, and that reducing the proprietary value of information already shared with suppliers weakens the incentive to maintain otherwise unproductive relationships.

[Insert Table 7 Here]

[Insert Figure 4 Here]

5.2 Leahy-Smith America Invents Act Reduced R&D Disclosure

Second, I exploit a reverse quasi-natural experiment, the enactment of the Leahy-Smith America Invents Act (AIA), which reduced public R&D disclosure and increased the proprietary value of information shared with supply chain partners. A key feature of the AIA was the shift from a first-to-invent to a first-to-file patent system for all patent applications filed on or after March 16, 2013. Under former regime, patents were granted to the "first and true" inventors, even if competitors filed similar patent applications earlier. In contrast, the first-to-file regime grants patent rights strictly based on filing date (i.e., being the first to file is essential to the granting of a patent), making premature disclosure of innovation information riskier, as rivals could preempt the application and permanently block patent rights. This shift raised the costs of publicly

disclosing R&D information, prompting innovation-intensive firms to disclose less to better safeguard intellectual property (Huang et al., 2021). Thus, by lowering the baseline level of public R&D disclosure, the AIA increased the marginal proprietary value of information shared with supply chain partners. Consequently, customers became more cautious about protecting information within existing supplier relationships, raising the cost of termination. I conjecture that customers affected by the AIA are more susceptible to lock-in induced by proprietary information sharing and thus less likely to terminate supplier relationships relative to unaffected firms.

To examine the effect of the AIA on supply chain termination, I employ a difference-in-differences design at the customer firm-year level over a ten-year window centered on the Act. The pre-event period is 2008-2012 ($AIA = 0$) and the post-event period is 2014-2018 ($AIA = 1$), excluding 2013 for cleaner identification. Following prior studies (e.g., Brown et al., 2009; Cao et al., 2018; Huang et al., 2021), I classify firms as innovation-intensive ($Treat_{AIA} = 1$) if their average R&D intensity exceeds the industry median during the sample period, and as non-innovation-intensive ($Treat_{AIA} = 0$) otherwise. Because many R&D-intensive firms do not patent (Koh and Reeb, 2015), I restrict the sample to firms with at least one patent application before 2018 to ensure meaningful exposure to the AIA. Consistent with the design in Section 5.1, the dependent variable is *Termination Num*, and the main independent variable is $Treat_{AIA} \times AIA$.

Table 7 Panel B presents the difference-in-differences results, showing that the coefficients on $Treat_{AIA} \times AIA$ are significantly negative across all specifications. The dynamic effects in Figure 4 Panel B further support the parallel trends assumption. These findings indicate that after the AIA, affected customers, those reducing public R&D disclosure, terminate fewer supplier relationships relative to unaffected firms. As the proprietary value of information shared with suppliers rises, customer firms face stronger incentives to maintain existing relationships, leading to fewer

supplier terminations. This evidence supports the interpretation that proprietary information sharing induces supply chain lock-in. Overall, the two quasi-natural experiments provide causal evidence that the proprietary nature of shared information locks customer firms into their suppliers.

6. Cross-Sectional Analyses

I conduct a series of cross-sectional tests to further strengthen the inference that proprietary cost concerns incentivize customer firms to lock in with their suppliers. First, I predict that lock-in effects are more pronounced when customer firms operate in highly competitive product markets, where incentives to safeguard proprietary information are stronger. Consistent with this prediction, when partitioning the sample by the Herfindahl-Hirschman Index (HHI) (*Compustat HHI*), I find that lock-in effects are concentrated among customer firms with lower HHI values (i.e., those facing more intense competition) (see Table 8 Panel A).[11]

Second, I expect lock-in effects to be more salient when customer firms' rivals engage in intensive innovation activity, as innovative rivals are better positioned to exploit leaked proprietary information. As Table 8 Panel B presents, partitioning the sample by customer firms' industry-level R&D intensity (*Ind R&D Intensity*) yields results consistent with this prediction.

Finally, I conjecture that lock-in effects are stronger when the focal supply chain relationship represents the sole conduit for proprietary information sharing, i.e., when no other ties exist between the supplier and customer, such as common institutional ownership (e.g., Freeman, 2025) or overlapping board members (e.g., Cheng et al., 2021). The cross-sectional results in Table 8 Panel C align with my predictions.

[Insert Table 8 Here]

[11] In untabulated robustness tests, my inferences are consistent when calculating HHI based on TNIC-3 industry (Hoberg et al., 2014).

7. Conclusions

The smooth functioning of supply chains is critical for economic stability and growth. While information sharing is a cornerstone of supply chain efficiency and resilience, it also entails significant risks and challenges. This paper examines whether customer-to-supplier proprietary information sharing constrains customer firms' flexibility to terminate supplier relationships when relationships become potentially unproductive, i.e., contributes to supply chain lock-in.

I develop a new, contract-based measure of customer-to-supplier proprietary information sharing, captured by the intensity of confidentiality provisions in supply chain agreements. Validation tests show that this measure correlates positively with customer firms' proprietary cost concerns and that higher-confidentiality-intensity contracts are associated with enhanced suppliers' managerial learning, specifically, improvements in information environments, investment, and innovation. These findings indicate that proprietary information obtained through supply chain interactions broadens suppliers' information sets and strengthens corporate decision-making, highlighting economic benefits beyond the operational coordination emphasized in prior research.

Consistent with supply chain lock-in effects, I find that relationships characterized by greater proprietary information sharing are longer-lasting and less likely to terminate following adverse supplier events (e.g., regulatory violations, exposure to import competition, and financial distress), consistent with reduced exit flexibility. Cross-sectional analyses further show that these lock-in effects are stronger when proprietary cost concerns are more salient, for example, when customer firms face intense product market competition, compete against highly innovative rivals, or when the focal relationship is the sole conduit for proprietary information exchange.

To address endogeneity concerns, I exploit two quasi-natural experiments that plausibly alter the proprietary value of information already shared with suppliers while leaving other existing

supply chain features such as input specificity unchanged. The AIPA accelerated patent disclosure, reducing the proprietary value of information already shared with suppliers. By contrast, the AIA led firms to curtail public R&D disclosure, increasing the proprietary value of information already shared with suppliers. I find that affected customer firms are more likely to terminate supplier relationships following the AIPA and less likely to do so following the AIA. These patterns are consistent with proprietary cost concerns as a key mechanism underlying supply chain lock-in.

Overall, these findings highlight the costs of proprietary information sharing in supply chains. While information exchange enhances managerial learning, it creates contractual frictions by raising switching costs and limiting exit flexibility. By providing a more nuanced understanding of the dual-edged nature of proprietary information sharing in supply chains, this study provides new insights into how private inter-firm information flows shape supply chain relationships.

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Appendix A
Variable definitions

This table provides a detailed description of the procedures used to compute each variable used in the analyses. Data are obtained through the SEC EDGAR, WRDS SEC Analytics Suite, FactSet Revere Supply Chain Relationships, DISCERN, United States Patent and Trademark Office (USPTO), Securities Data Company, Violation Tracker, Exhibit 21 of Form 10-K, S&P Capital IQ, I/B/E/S, LSEG Institutional 13F Holdings, BoardEx, Compustat, and CRSP. All continuous variables are winsorized at the 1st and 99th percentiles of their distributions.

Primary dependent variables:

Variable	Definition
Conf Word Num	The number of words in confidentiality-related sections of the contract.
Conf Word Ratio	The number of words in confidentiality-related sections scaled by the total word count of the entire supply chain contract.
Termination	An indicator variable equal to one if the supply chain relationship gets terminated in the current year, and zero otherwise.
Termination Num	The natural log of one plus the number of supply chain relationship terminations for the customer firm in the current year.

Primary independent and control variables:

Variable	Definition
R&D	The firm's research and development expense in the current fiscal year scaled by total assets at the prior fiscal year-end.
Trade Secret	The natural log of one plus the number of the firm's 10-K filing mentions of "trade secret" or "trade secrecy" in the current fiscal year. Trade secret data is obtained from Glaeser (2018).
Patent	The natural log of one plus the number of patents in the past three years. Patent data are from the USPTO and DISCERN (Arora et al., 2024a, 2024b).
Same Industry	An indicator variable equal to one if the customer and supplier firms are in the same two-digit SIC industry, and zero otherwise.
Customer Power	An indicator variable equal to one if the customer firm size is larger than the supplier firm size at the prior fiscal year-end, and zero otherwise.
Intangible	The firm's intangible assets scaled by total assets at the prior fiscal year-end.
ROA	The firm's net income for the current fiscal year scaled by total assets at the prior fiscal year-end.
Leader	An indicator variable equal to one if the firm's sales is top 5 within the two digit-SIC industry-year, and zero otherwise.
Size	The natural log of the firm's book value of assets at the prior fiscal year-end.
Age	The natural log of the firm's age. The firm's age is computed as the number of years since the firm first entered Compustat.
Lev	The firm's long-term debt and short-term debt scaled by total assets at the prior fiscal year-end.
Total Word Num Ln	The natural log of the total number of words in the supply chain contract.
Duration Ex-Ante	The natural log of the number of years between the date that the contract commences to the date of expiry, as specified in the contract.
Renewal	An indicator variable equal to one if the contract contains a clause that the contract is automatically renewed unless either party explicitly terminates the contract, and zero otherwise.
Demand Forecast	An indicator variable equal to one if the customer contractually commits to regularly provide its private forecasts to the supplier, and zero otherwise.
Supplier Violation	The natural log of one plus the supplier firms' total regulatory penalty in the current year.
Loss	An indicator variable equal to one if the firm's net income for the current fiscal year is negative, and zero otherwise.
Cash	The firm's cash and short-term investments scaled by total assets at the prior fiscal year-end.

Supplier Import Comp	An indicator variable equal to one if the supplier firm operates in an industry that experiences a large tariff rate reduction during its relationship with the customer firm, and the observation year is the same as or follows the year of the tariff reduction event, and zero otherwise. Large tariff rate reduction events are identified following Huang et al. (2017).
Supplier Fin Distress	An indicator variable equal to one if the supplier firm's probability of default is higher than 10% in the current year, and zero otherwise. Following Merton (1974), the distance to default (DD) is calculated as $DD = \frac{\ln\left(\frac{V}{F}\right)+(\mu-0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$, where $V = Debt + VN(d_1) - e^{-rT}DebtN(d_2)$, $d_1 = \frac{\ln\left(\frac{V}{F}\right)+(r+0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}$, $d_2 = d_1 - \sigma_V\sqrt{T}$. Probability of default is $\pi_{Merton} = N(-DD)$. I use an iterative approach to estimate π_{Merton} (Bharath and Shumway, 2008).
Conf Word Decile	The decile rank of *Conf Word Ratio*.
Input Specificity	The total number of words in the "Product Specifications" section of the contract.
Material Supplier	An indicator variable equal to one if the filer firm of the contract is the customer firm, and zero otherwise.
Treat$_{AIPA}$	An indicator variable equal to one if the firm is within the top three deciles of the measure of information spill-outs, and zero otherwise. The measure of information spill-outs is constructed following Kim and Valentine (2021).
AIPA	An indicator variable equal to one if the fiscal year is after the AIPA effective year, 2000, and zero otherwise.
Treat$_{AIA}$	An indicator variable equal to one if the firm's average R&D intensity during 2008-2018 (excluding 2013) is above the 2-digit SIC industry median, and zero otherwise.
AIA	An indicator variable equal to one if the fiscal year is after the AIA effective year, 2013, and zero otherwise.
Compustat HHI	The summation of the squares of the market shares of all firms in the same 2-digit SIC industry in the current year.
Ind R&D Intensity	The industry-level total research and development expense scaled by total assets in the current year.
Common Owner/Director	An indicator variable equal to one if the supplier and the customer have common institutional blockholders or common board of directors, and zero otherwise.

Additional variables in Online Appendix:

Variable	Definition
Treat	An indicator variable equal to one if the firm enters into a supply chain contract with the top tercile of the confidentiality intensity distribution (defined based on *Conf Word Ratio*) during the sample period, and zero otherwise.
Post	An indicator variable equal to one if the fiscal year is after the treatment firm enters into a supply chain contract with the top tercile of the confidentiality intensity distribution, and zero otherwise.
EA Speed	The natural log of the number of days between the end of the fiscal year and the firm's earnings announcement.
Mgmt Forecast Issue	An indicator variable equal to one if the firm management issues an annual EPS forecast for the current fiscal year, and zero otherwise.
Mgmt Forecast Error	The absolute value of (the firm management's last available estimate of EPS before year-end minus actual EPS) scaled by actual EPS.
Mgmt Forecast Width	The firm management EPS forecast width for a range or point forecast, calculated as the difference between the high-end estimate and the low-end estimate, scaled by the absolute value of the mid-point of the estimate. Width is zero for a point forecast.
Investment	The firm's total investment in the next fiscal year, calculated as the sum of R&D expenditure, capital expenditure, and acquisition expenditure less cash receipts from sale of property, plant, and equipment, scaled by lagged total assets,
Over Firm	The average of the firm's two decile ranks of its cash balances and (negative) leverage by industry and year. This measure is scaled to the range of zero and one.

Invest Inefficiency	The absolute value of residuals from a firm-level regression of future capital investment on current-year sales growth, following Biddle et al. (2009). Specifically, for each Fama-French 48-industry-year with at least 20 observations, the following regression is estimated: $Investment_{i,t+1} = \beta_0 + \beta_1 Sales\ Growth_{i,t} + \varepsilon_{i,t+1}$; where $Investment_{i,t+1}$ is the firm's total investment in fiscal year $t+1$, calculated as the sum of R&D expenditure, capital expenditure, and acquisition expenditure less cash receipts from sale of property, plant, and equipment, scaled by lagged total assets, then multiplied by 100. $Sales\ Growth_{i,t}$ is the firm's annual sales growth rate for from year $t-1$ to year t.
Acquisition CAR [-1,+1]	The three-day [-1, +1] cumulative abnormal return of the acquiring firm surrounding the acquisition announcement date. The abnormal return is calculated using Fama-French three-factor model.
Patent Value	The private, economic value of innovation, deflated to 1982 (million) dollars using the CPI, estimated by Kogan et al. (2017). Kogan et al. (2017) calculate patent values using excess stock returns of the filing company around the patent publication date.
Duration Ex-Post	The natural log of the number of years between the starting date and ending date of the supply chain relationship.
Supplier Violation Alt	The supplier firms' total regulatory penalty scaled by total assets in the current year.
Supplier Fin Distress Alt	An indicator variable equal to one if the supplier firm has an Ohlson O-score in the top decile in the current year, and zero otherwise. Ohlson's O-score is calculated following Ohlson (1980).

Appendix B
Examples of excerpts of confidentiality provisions in supply chain contracts

Example 1: Suneva Medical Inc. ("buyer") and Merit Medical Systems Inc. ("seller")

Article 7 CONFIDENTIALITY

7. 1 Confidential Information. Merit and Customer may have access to each other's Confidential Information during the Term of this Agreement. For the purposes of this Agreement, "Confidential Information" means any and all information or proprietary materials (in every form and media) not generally known in the relevant trade or industry made available by either Party (in such case, the "Disclosing Party") to the other (in such case, the "Receiving Party") and which the Disclosing Party designates as confidential or may reasonably be understood as confidential, including but not limited to Product information, regulatory documentation (including licenses, permits, and applications, U.S. Food and Drug Administration applications, substantial equivalence determination letters, U.S. pre-market approvals, investigation device exemptions, international registrations, CE dossiers, technical files, and any amendments to the foregoing), existing or contemplated products, designs, inventions, technology, processes, know-how, trade secrets, technical data, engineering, specifications, techniques, methodologies and concepts, and any information related thereto, and information relating to vendors, agreements, customer information, pricing, quality systems, strategic and tactical plans, business plans, sales and marketing plans, testing data, research and development, clinical literature, clinical trial data, communications with physicians, internal or external inspection/audit reports, and corrective action plans. The Receiving Party will maintain Confidential Information in confidence using the same standard of care it uses to maintain its own Confidential Information, but in any case no less than reasonable care, and will not use such information for itself or others except as provided in this Agreement. Such obligation of confidentiality and non-use shall not apply to information which (a) is known to the Receiving Party prior to the disclosure as demonstrated by documentary evidence; (b) is publicly known as of the date of the disclosure; (c) becomes publicly known after the date disclosure through no fault of the Receiving Party; (d) is received by the Receiving party from a third party who has, to the Receiving Party's knowledge, no obligation of confidentiality to the Disclosing party; or (e) is independently developed by the Receiving party without reference to or use of the Disclosing Party's Confidential Information, as demonstrated by documentary evidence. The restrictions on disclosure contained in this Section 7.1 shall not apply to any information which is required to be disclosed by a valid court rule or governmental law or regulation, provided that the Receiving Party gives the Disclosing Party prompt notice of any such requirement and cooperates with the Disclosing Party in attempting to limit such disclosure and obtain confidential treatment thereof.

7.2 Obligations Upon Termination. Upon termination of this Agreement, each Party shall return to the other all Confidential Information of the other Party within thirty (30) days after notice of termination, except for Confidential Information which is embodied in documents or records that the Receiving Party is required to retain under applicable law and regulation.

7.3 Remedies. The Parties acknowledge that monetary damages may be an inadequate remedy for any breach by a Party of its obligations under this Article 7 and that the non-breaching Party shall be entitled to seek injunctive relief to enforce the breaching Party's obligations, in addition to any other remedies the non-breaching Party may be entitled to.

Example 2: Lifestream Technologies Inc. ("buyer") and Roche Diagnostics GmbH ("seller")

21 CONFIDENTIALITY

21.1 Throughout the term of the Agreement and for a period of five years following the termination thereof, each party hereto agrees to hold in strict confidence and not disclose to any third party any and all information received by one party from the other pursuant to this Agreement including, but not limited to any technology, know-how, processes or patent application disclosed by the other or derived from information thus disclosed, trade secrets, inventions, ideas, data, manufacturing or finance matters. Each party furthermore agrees that it may only use such information received from the other to the extent required to accomplish the purposes of this Agreement and to restrict access to such information to persons entrusted to carry out the activities provided for hereunder who are subject to an analogous confidentiality obligation. Each party agrees to clearly mark as confidential any and all information which it makes

available to the other party which the disposing party considers to be confidential. Each party furthermore agrees to reduce to writing any such confidential information which it discloses orally and to provide the receiving party with a copy thereof within thirty (30) days of the date of the oral disclosure.

21.2 The confidentiality obligations pursuant to clause 17.1 shall not apply to information which:

21.2.1 is in the public domain at the time of its disclosure;

21.2.2 is published or otherwise becomes part of the public domain through no fault of the receiving party or becomes available from a third party who has the right to disclose it;

21.2.3 was in the possession of the receiving party at the time of its disclosure as shown by prior written records;

21.2.4 was or will be independently developed by employees of the receiving party who had no access to the information disclosed; or

21.2.5 must be disclosed in accordance with applicable laws or in order to obtain Government Approval in accordance with the terms of this Agreement.

21.3 Neither party shall make any press release or other similar public announcement concerning the executed Agreement without the prior written consent of the other party hereto, such approval not to be unreasonably withheld, except as required by law. Approval will be deemed granted if no response is received by the proposing party within ten (10) working days of its delivery of a request for approval to the other.

Example 3: The Hershey Company ("buyer") and Barry Callebaut AG ("seller")

7. CONFIDENTIALITY

A. "Confidential Information" shall mean Proprietary Information and Trade Secret Information. With respect to information disclosed by Hershey to Callebaut, Confidential Information shall mean non-public information, including, without limitation, all information Callebaut may receive, or has received since September 1, 2006, from Hershey concerning the processing of, production of, marketing of, distribution of, selling of, strategic plans of, recipes for and quantities of the Products Hershey requests Callebaut to process and package and any recipes, ingredients, suppliers, product specifications, production output, sales volume, consumer insights, costing/financial information, productivity, research/developmental activities, location of manufacturing or Hershey manufacturing processes used in the production of the Products. With respect to information disclosed by Callebaut to Hershey, Confidential Information shall mean non-public information, including, without limitation, all information Hershey may receive, or has received since September 1, 2006, from Callebaut concerning Callebaut's facilities, financial and production capabilities, processing of, production of, marketing of, distribution of selling of and strategic plans of Callebaut products and any recipes, ingredients, suppliers, product specifications, production output, sales volume, costing/financial information, productivity and research/developmental activities.

…

Example 4: Calumet Lubricants Co. ("buyer") and Legacy Resources Co. ("seller")

13. Confidentiality. The Parties agree that the existence of this Agreement and the discussions contemplated hereby are strictly confidential. Accordingly, neither Party shall make or issue any public statement, announcement or disclosure with respect to the existence or terms of this Agreement without the prior written approval of the other, and the discussions between the Parties shall remain confidential, except to the extent that disclosure is otherwise required by law, the rules of any applicable stock exchange or judicial process.

Example 5: Pacesetter Inc. ("buyer") and NVE Corporation ("seller")

9. Confidential information. Seller will keep proprietary information and technology that Buyer discloses to Seller in strict secrecy and confidence. Seller will not disclose it to third parties. Seller will not use it for Seller's own benefit other than for performing Seller's duties under this Agreement. Seller will ensure that Seller's employees sign agreements requiring them to keep confidential the information they learned about Buyer in their positions with Seller. These agreements will require them to keep confidential Buyer's proprietary information about the products. Seller

will not supply proprietary information or materials relating to products to any other person or entity without Buyer's prior written approval, except to the FDA and similar regulatory agencies.

9.1. Seller will be excused from its confidential information duties to the extent that any of the information: (i) was already in the public domain when Buyer disclosed it to Seller; (ii) enters the public domain through no fault of Seller; (iii) was in Seller's possession before Buyer disclosed it to Seller and Seller did not receive it from Buyer or a third party who was obligated to Buyer to keep it confidential; (iv) was later received by Seller from a third party who was not obligated to Buyer to keep it confidential; or (v) Seller discloses pursuant to a judicial requirement, so long as Seller notifies Buyer immediately when Seller learns of the judicial action.
…

Example 6: Mannatech Incorporated ("buyer") and Natural Alternatives Inc. ("seller")

11. Confidential Information.
11.1 Seller recognizes and acknowledges that Buyer's trade name(s), trademarks, copyrights, patents, marketing plans, identity of and related information regarding its Associates, product formulations and other proprietary product information and any information relating to the management/operations of Buyer are valuable assets belonging to Buyer and as such are the sole property and may constitute trade secrets of Buyer. Prior to and during the performance of this Agreement, Seller may have or had access to certain confidential information pertaining to Buyer. Seller specifically agrees Seller will not at any time, during or after the performance of this Agreement, in any manner, either directly or indirectly, use, divulge, disclose, or communicate to any person, firm or corporation, any confidential information of any kind, nature, or description concerning any matters affecting or relating to the business of Buyer (hereinafter referred to as "Buyer Confidential Information"). Buyer Confidential Information includes but is not limited to: Buyer genealogies (being the information held by Buyer in connection with any current or former Associate of Buyer) related to its Associates including without limitation its relationship with each of its Associates, the Associate's name, upline and downline, charts, data reports, proprietary product information which may from time-to-time be made known to Seller, the names or practices of any of Buyer's customers or Associates; Buyer's marketing methods and related data; the names of Buyer's vendors or suppliers; costs of materials; costs of its products generally, the prices Buyer obtains or has obtained or at which it sells or has sold its products or services; manufacturing and sales costs; lists or other written records used in Buyer's business; compensation paid to its Associates, details of training methods, new products or new uses for old products, merchandising or sales techniques, contracts and licenses, business systems, computer programs, or any other confidential information of, about, or concerning the business of Buyer; its manner of operation or other confidential data of any kind, nature or description.
…

Figure 1
Word cloud of confidentiality sections in supply chain contracts

This figure presents a word cloud of confidentiality-related sections in supply chain contracts. Larger font size indicates higher word frequency.

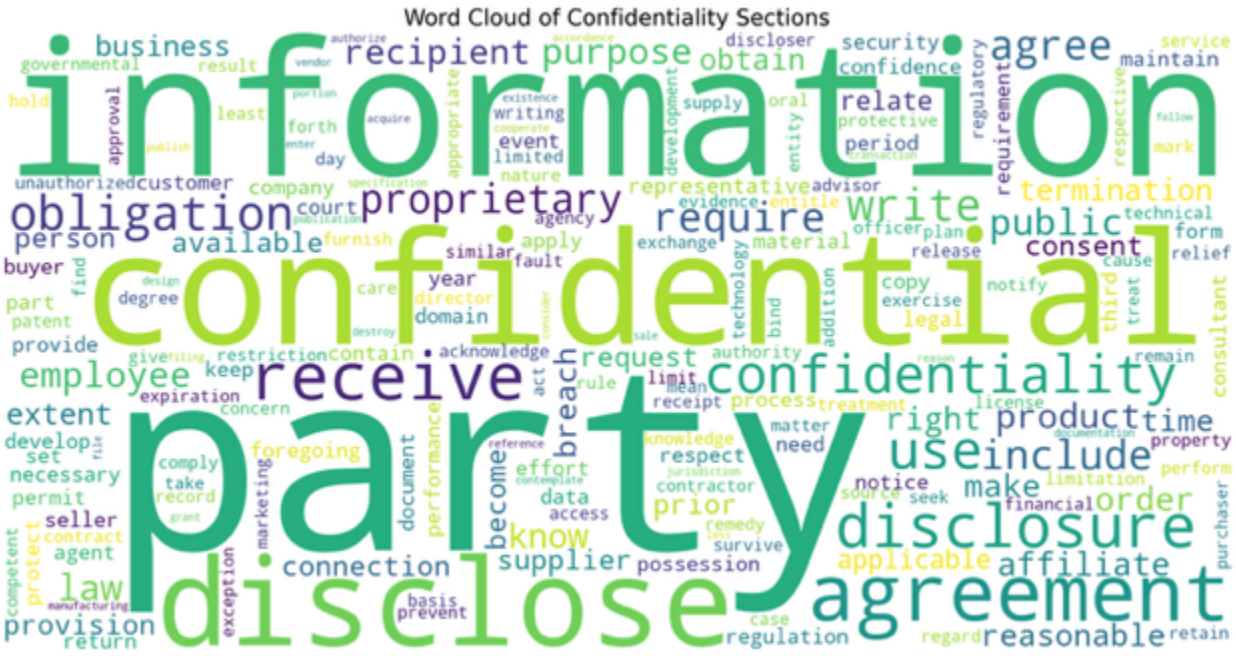


Figure 2
Categories of proprietary information in supply chain contract confidentiality sections

This figure presents the proportion of different categories of proprietary information disclosed in supply chain contract confidentiality sections. Note: The summation of all categories exceeds 100% because a contract may disclose multiple categories of proprietary information.

- **Generic**: trade secret, proprietary information, confidential information, private information
- **Strategy**: business affair, business information, business plan, business strategy, marketing plan, strategy, tactical plan, action plan
- **Regulation**: audit, certification, international registration, license, regulatory documentation, reports
- **R&D**: R&D, research and development, patent, patent application, FDA, clinical trial, intellectual property, know-how, concept, idea, invention, apparatus, business system, computer program, engineering specification, facility information, manufacturing data, merchandising technique, method, procedure, process, sample, technical file, technical information, technology, test data, test result, training method
- **Product**: demand, forecast, pricing, product formulation, product data, product information, product specification, production output, productivity, quality system, sales technique, sales volume
- **Personnel**: personnel, human resource
- **Financial**: accounting, budget, compensation, cost, financial condition, financial statement, financial information, financial matter
- **Consumer**: consumer data, consumer insight

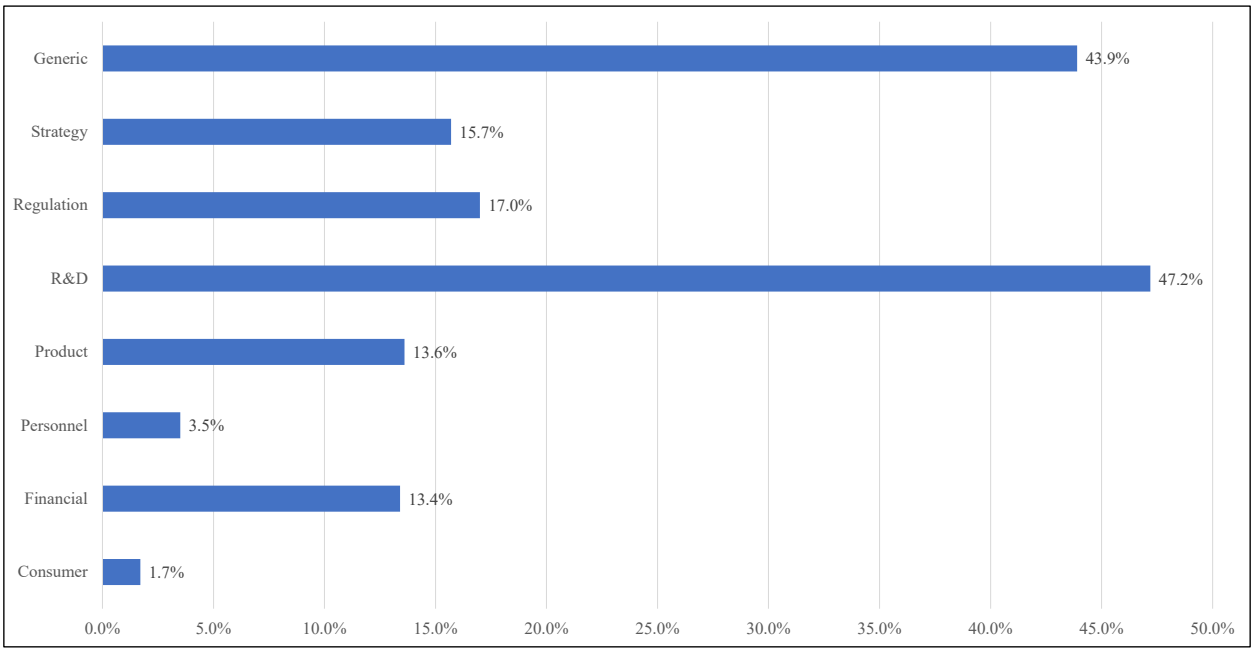


Figure 3
Average confidentiality section intensity by contract entering year

This figure plots the average confidentiality section intensity by contract entering year.

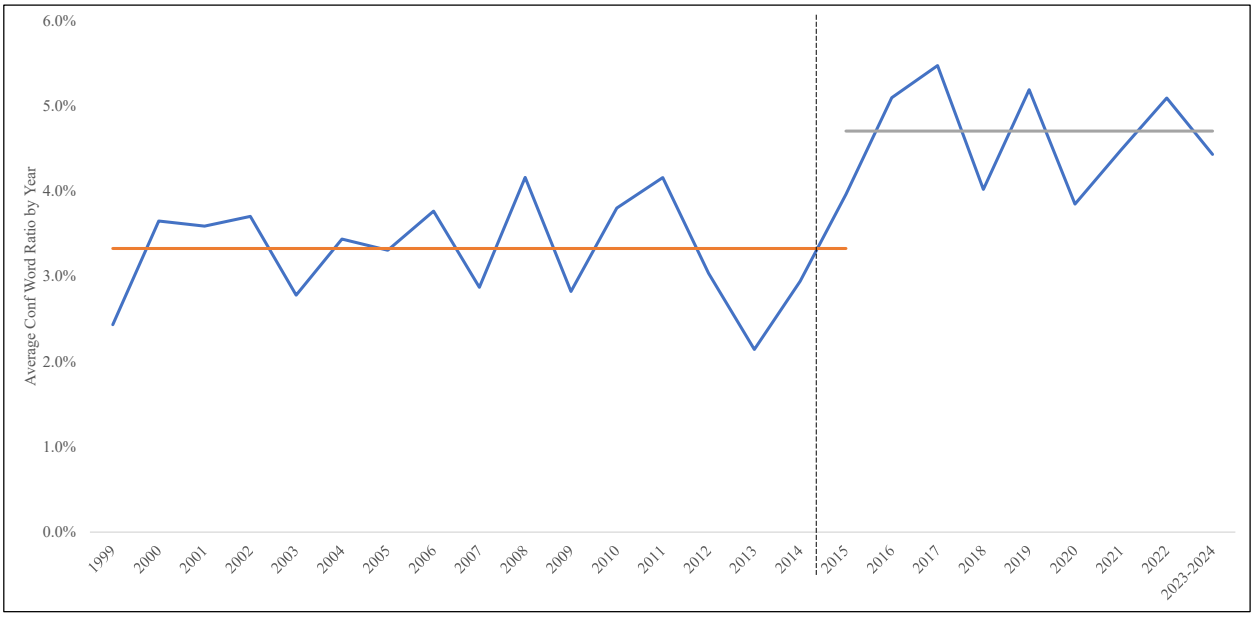
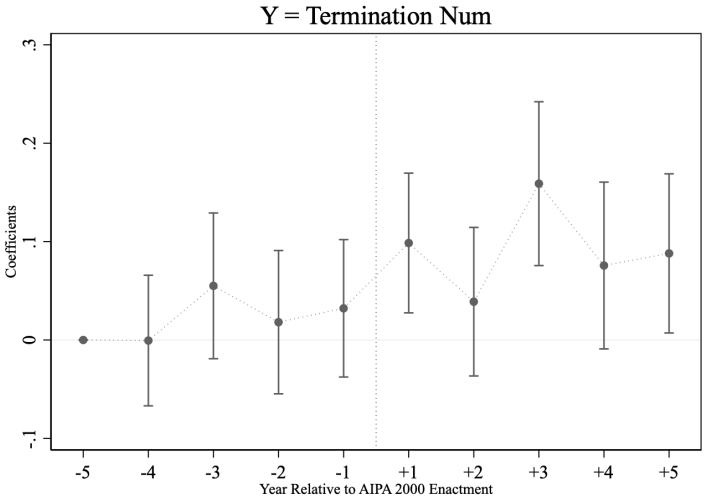


Figure 4
Dynamic effect of two quasi-natural experiments on supply chain relationship terminations

The figures display the effect of two quasi-natural experiments that change the proprietary value of information shared with suppliers in event time. Panel A displays the dynamic effect of the American Inventors Protection Act on supply chain relationship terminations, using a customer firm-year level sample from 1995-2005 (excluding 2000). Panel B displays the dynamic effect of the Leahy-Smith America Invents Act on supply chain relationship terminations, using a customer firm-year level sample from 2008-2018 (excluding 2013). Formally, I estimate $Termination\ Num_{i,t} = \alpha + \sum_{n=t-4, n\neq t}^{t+5} \beta_{k1}\ Treat_i \times Year\ n_t + \beta_k Controls + \delta_i + \gamma_{ind \times t} + \epsilon_{i,t}$, where δ_i and $\gamma_{ind \times t}$ represent firm and industry × fiscal year fixed effects, respectively. *Year t-4* to *Year t+5* are indicator variables for event years *t-4* through *t+5*. Each point estimate is accompanied by a 90% confidence interval calculated based on standard errors clustered by industry. Note that *Year t-5* has a coefficient of zero and no confidence interval because it serves as the benchmark period. All variables are defined in Appendix A.

Panel A: American Inventors Protection Act (AIPA)



Panel B: Leahy-Smith America Invents Act (AIA)

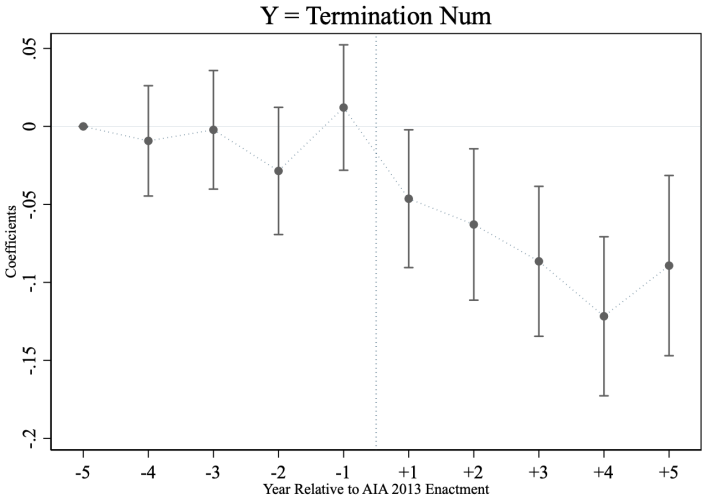


Table 1
Contract-level sample selection

This table presents the selection procedure of the main sample of supply chain contracts entering during 1999 to 2024.

Description	No. of contracts dropped	No. of contracts remaining
All supply chain contracts filed during years 2000-2024		5,221
Keep contracts entering during years 1999-2024	(278)	4,943
Exclude contracts with neither suppliers nor customers identified in Compustat	(167)	4,776
Exclude contracts with either suppliers or customers in financial industry	(86)	4,690
Exclude contracts with neither suppliers nor customers having assets data in Compusta	(587)	4,103
Final sample of contracts		**4,103**
Final sample of unique public supplier firms in contracts		**848**
Final sample of unique public customer firms in contracts		**1,139**

Table 2
Contract-level descriptive statistics

This table presents descriptive information for the sample distribution and variables of interest. Panel A presents the descriptive statistics of the sample of supply chain contracts during 1999 to 2024. Panel B presents the contract sample distribution of firms' public listing status. Panel C presents the contract sample distribution by the customer firm Fama-French 48-industry. Panel D presents the contract sample distribution by the supplier firm Fama-French 48-industry. Details of variable construction are contained in Appendix A.

Panel A: Contract and firm characteristics

Variables	N	Mean	SD	P25	P50	P75
Contract characteristics:						
Conf Word Num	4,103	317.458	287.033	72.000	269.000	490.000
Conf Word Ratio	4,103	0.035	0.034	0.010	0.025	0.050
Total Word Num Ln	4,103	8.987	0.805	8.436	9.037	9.529
Duration Ex-Ante (Raw)	4,103	4.885	3.749	3.000	5.000	5.000
Duration Ex-Ante	4,103	1.380	0.670	1.099	1.609	1.609
Renewal	4,103	0.573	0.495	0.000	1.000	1.000
Demand Forecast	4,103	0.606	0.489	0.000	1.000	1.000
Customer and supplier firm characteristics:						
R&D Cus	3,064	0.102	0.216	0.000	0.008	0.098
R&D Sup	2,438	0.076	0.165	0.000	0.008	0.092
Trade Secret Cus	3,740	0.753	0.952	0.000	0.000	1.609
Trade Secret Sup	3,208	0.674	0.905	0.000	0.000	1.386
Patent Cus	3,740	0.962	1.905	0.000	0.000	1.099
Patent Sup	3,208	1.232	2.112	0.000	0.000	1.946
Same Industry	2,536	0.390	0.488	0.000	0.000	1.000
Customer Power	1,399	0.417	0.493	0.000	0.000	1.000
Intangible Cus	3,064	0.085	0.141	0.000	0.004	0.115
Intangible Sup	2,438	0.067	0.122	0.000	0.007	0.074
ROA Cus	2,994	-0.314	1.230	-0.230	0.019	0.058
ROA Sup	2,415	-0.154	0.687	-0.104	0.031	0.070
Leader Cus	3,186	0.067	0.249	0.000	0.000	0.000
Leader Sup	2,536	0.095	0.293	0.000	0.000	0.000
Size Cus	3,064	6.335	2.805	4.288	6.636	8.332
Size Sup	2,438	6.851	2.768	4.781	7.180	9.088
Age Cus	3,186	10.530	6.235	5.000	11.000	15.000
Age Sup	2,536	10.994	6.109	5.000	12.000	15.000
Lev Cus	2,895	0.280	0.307	0.041	0.238	0.386
Lev Sup	2,345	0.267	0.271	0.077	0.218	0.369

Panel B: Distribution of firms' public listing status

No. of contracts	Private Customer	Public Customer	Total
Private Supplier	0	1,665	1,665
Public Supplier	1,039	1,399	2,438
Total	1,039	3,064	4,103

Table 2 (continued)

Panel C: Customer firms' industry distribution

Fama-French 48 Industry	Freq.	Percent (%)	Conf Word Num	Conf Word Ratio
Agriculture	2	0.05	207.500	0.033
Food Products	140	3.41	240.686	0.039
Candy & Soda	12	0.29	199.000	0.028
Beer & Liquor	16	0.39	184.063	0.027
Tobacco Products	4	0.10	623.000	0.093
Recreation	13	0.32	414.692	0.042
Entertainment	14	0.34	221.214	0.074
Printing and Publishing	2	0.05	609.500	0.129
Consumer Goods	46	1.12	339.848	0.047
Apparel	3	0.07	201.667	0.047
Healthcare	30	0.73	276.100	0.039
Medical Equipment	194	4.73	380.778	0.050
Pharmaceutical Products	832	20.28	472.957	0.041
Chemicals	40	0.97	279.125	0.031
Rubber and Plastic Products	39	0.95	267.385	0.038
Textiles	3	0.07	268.333	0.033
Construction Materials	37	0.90	102.405	0.027
Construction	10	0.24	291.700	0.057
Steel Works Etc	59	1.44	344.915	0.034
Machinery	39	0.95	99.103	0.014
Electrical Equipment	33	0.80	372.303	0.062
Automobiles and Trucks	33	0.80	349.182	0.039
Aircraft	25	0.61	326.480	0.031
Shipbuilding, Railroad Equipment	3	0.07	626.000	0.074
Defense	2	0.05	421.000	0.053
Non-Metallic and Industrial Metal Minin	6	0.15	165.333	0.029
Coal	12	0.29	217.167	0.034
Petroleum and Natural Gas	113	2.75	284.469	0.025
Utilities	456	11.11	123.379	0.012
Communication	95	2.32	348.284	0.031
Personal Services	20	0.49	286.950	0.049
Business Services	138	3.36	279.725	0.036
Computers	84	2.05	385.333	0.034
Electronic Equipment	271	6.60	332.483	0.036
Measuring and Control Equipment	36	0.88	294.194	0.037
Business Supplies	23	0.56	191.043	0.016
Shipping Containers	14	0.34	572.000	0.083
Transportation	56	1.36	119.411	0.013
Wholesale	77	1.88	180.597	0.023
Retail	109	2.66	187.560	0.027
Restaraunts, Hotels, Motels	6	0.15	534.167	0.051
Almost Nothing	39	0.95	284.564	0.029
Missing	917	22.35	327.969	0.038
Total	**4,103**	**100.00**	**317.458**	**0.035**

Table 2 (continued)

Panel D: Supplier firms' industry distribution

Fama-French 48 Industry	Freq.	Percent (%)	Conf Word Num	Conf Word Ratio
Agriculture	1	0.02	310.000	0.070
Food Products	68	1.66	123.985	0.015
Candy & Soda	2	0.05	262.000	0.042
Beer & Liquor	2	0.05	293.000	0.054
Tobacco Products	1	0.02	281.000	0.058
Recreation	8	0.19	593.375	0.034
Entertainment	2	0.05	50.500	0.013
Printing and Publishing	2	0.05	569.500	0.078
Consumer Goods	15	0.37	387.067	0.063
Apparel	3	0.07	258.667	0.020
Healthcare	21	0.51	329.810	0.053
Medical Equipment	104	2.53	411.923	0.043
Pharmaceutical Products	616	15.01	428.292	0.036
Chemicals	89	2.17	272.079	0.041
Rubber and Plastic Products	34	0.83	321.088	0.045
Textiles	2	0.05	698.000	0.132
Construction Materials	36	0.88	84.389	0.021
Construction	6	0.15	63.000	0.029
Steel Works Etc	68	1.66	384.853	0.045
Fabricated Products	3	0.07	102.333	0.010
Machinery	82	2.00	354.512	0.069
Electrical Equipment	48	1.17	477.146	0.025
Automobiles and Trucks	20	0.49	318.700	0.033
Aircraft	6	0.15	470.333	0.061
Defense	2	0.05	0.000	0.000
Precious Metals	2	0.05	90.500	0.023
Non-Metallic and Industrial Metal Minin	15	0.37	542.067	0.068
Coal	36	0.88	117.361	0.016
Petroleum and Natural Gas	53	1.29	225.038	0.022
Utilities	388	9.46	78.745	0.014
Communication	57	1.39	411.298	0.034
Personal Services	7	0.17	184.857	0.012
Business Services	117	2.85	285.521	0.029
Computers	46	1.12	477.978	0.048
Electronic Equipment	302	7.36	347.702	0.036
Measuring and Control Equipment	35	0.85	284.657	0.029
Business Supplies	20	0.49	248.000	0.030
Shipping Containers	51	1.24	279.647	0.039
Transportation	5	0.12	134.600	0.016
Wholesale	101	2.46	194.139	0.021
Retail	16	0.39	224.375	0.049
Almost Nothing	44	1.07	314.227	0.040
Missing	1,567	38.19	339.252	0.038
Total	**4,103**	**100.00**	**317.458**	**0.035**

Table 3
Determinants of confidentiality provision intensity

This table presents the determinant tests of confidentiality provision intensity in supply chain contracts, using *Conf Word Ratio* as the dependent variable. Columns 1, 3, 5, and 7 include year fixed effects, and columns 2, 4, 6, and 8 include year, supplier industry, and customer industry fixed effects. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by both industries. The sample consists of contract-level observations from years 1999-2024. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dependent variable:		*Conf Word Ratio*							
	Pr. Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D Cus	+	0.025***	0.015***					0.017***	0.012***
		(5.95)	(5.31)					(5.15)	(3.68)
R&D Sup	+	0.018*	0.012					0.002	0.005
		(1.91)	(1.11)					(0.22)	(0.51)
Trade Secret Cus	+			0.003***	0.002***			0.002**	0.002***
				(3.21)	(3.72)			(2.58)	(3.57)
Trade Secret Sup	+			0.002	0.003**			0.001	0.002**
				(1.48)	(2.56)			(0.68)	(2.29)
Patent Cus	+					0.002***	0.001**	0.001***	0.001**
						(5.06)	(2.44)	(3.93)	(2.07)
Patent Sup	+					0.002***	0.001	0.001***	0.000
						(4.61)	(1.15)	(4.32)	(1.12)
Same Industry		-0.005**	-0.002	-0.005**	-0.002	-0.004	-0.002	-0.005*	-0.002
		(-2.47)	(-0.83)	(-2.15)	(-1.03)	(-1.38)	(-1.09)	(-1.99)	(-0.91)
Customer Power		0.003	0.000	0.003	0.001	0.003	0.001	0.003	0.001
		(0.93)	(0.09)	(1.06)	(0.14)	(0.95)	(0.25)	(0.92)	(0.18)
Intangible Cus		0.005	-0.004	0.006	-0.003	0.005	-0.004	0.008	0.001
		(0.66)	(-0.78)	(0.87)	(-0.56)	(0.65)	(-0.75)	(1.17)	(0.21)
Intangible Sup		-0.003	0.004	-0.008	-0.000	0.002	0.004	-0.001	0.000
		(-0.23)	(0.31)	(-0.60)	(-0.04)	(0.18)	(0.31)	(-0.12)	(0.03)
ROA Cus		0.005*	0.002	0.001	-0.001	0.001	-0.001	0.005*	0.002
		(1.83)	(0.47)	(0.56)	(-0.20)	(0.24)	(-0.34)	(1.96)	(0.76)
ROA Sup		0.000	0.001	0.000	0.000	-0.000	-0.000	0.000	0.001
		(0.21)	(0.26)	(0.10)	(0.16)	(-0.18)	(-0.14)	(0.04)	(0.36)
Leader Cus		0.011**	0.010*	0.011**	0.010**	0.006	0.007	0.006	0.007
		(2.46)	(1.92)	(2.45)	(2.17)	(1.47)	(1.45)	(1.47)	(1.58)
Leader Sup		-0.005	-0.003	-0.004	-0.003	-0.006**	-0.004	-0.006**	-0.004
		(-1.69)	(-1.23)	(-1.34)	(-1.01)	(-2.10)	(-1.65)	(-2.20)	(-1.34)
Size Cus		-0.002***	-0.000	-0.003***	-0.000	-0.003***	-0.001	-0.003***	-0.001
		(-3.35)	(-0.56)	(-3.96)	(-0.65)	(-5.21)	(-1.46)	(-4.80)	(-1.16)
Size Sup		-0.000	0.000	-0.001	0.000	-0.001**	-0.000	-0.001	0.000
		(-0.71)	(0.72)	(-0.85)	(0.77)	(-2.24)	(-0.04)	(-1.38)	(0.36)
Age Cus		-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
		(-0.03)	(-0.24)	(-0.19)	(-0.41)	(-0.44)	(-0.64)	(-0.44)	(-0.67)
Age Sup		-0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000
		(-0.08)	(0.21)	(-0.44)	(-0.09)	(-0.45)	(0.03)	(-0.61)	(-0.11)
Lev Cus		0.004	0.004	0.004	0.004	0.005	0.003	0.006	0.003
		(0.68)	(1.06)	(0.65)	(1.13)	(0.90)	(0.90)	(1.03)	(0.99)
Lev Sup		0.004	0.004	0.004	0.005	0.006	0.003	0.007	0.005
		(0.29)	(0.46)	(0.28)	(0.51)	(0.41)	(0.30)	(0.57)	(0.47)
Total Word Num Ln		-0.003	-0.005	-0.002	-0.004	-0.002	-0.004	-0.003	-0.005
		(-1.26)	(-1.51)	(-0.82)	(-1.38)	(-1.23)	(-1.43)	(-1.46)	(-1.50)
Duration Ex-Ante		-0.001	-0.002	-0.001	-0.003	-0.001	-0.002	-0.001	-0.002
		(-0.87)	(-1.41)	(-1.10)	(-1.61)	(-1.05)	(-1.70)	(-1.08)	(-1.50)
Renewal		0.007***	0.005**	0.007***	0.006***	0.006***	0.005**	0.006***	0.006**
		(3.83)	(2.67)	(3.79)	(3.37)	(3.07)	(2.30)	(3.29)	(2.71)
Demand Forecast		0.000	0.000	-0.000	-0.001	0.000	-0.000	-0.001	-0.001
		(0.01)	(0.01)	(-0.07)	(-0.20)	(0.01)	(-0.02)	(-0.18)	(-0.19)
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier Industry FE		No	Yes	No	Yes	No	Yes	No	Yes
Customer Industry FE		No	Yes	No	Yes	No	Yes	No	Yes
S.E. clustered by both industries		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations		1,249	1,238	1,249	1,238	1,249	1,238	1,249	1,238
Adj. R-Squared		0.128	0.253	0.125	0.259	0.143	0.253	0.152	0.263

Table 4
Proprietary information sharing and supply chain relationship termination: Suppliers' regulatory violations

This table presents the results examining the effect of potential proprietary information sharing on supply chain relationship termination likelihood in the case of suppliers' adverse events, focusing on suppliers' regulatory violations. The dependent variable is the indicator variable of supply chain relationship termination (*Termination*), and the sample is at firm pair-year level from years 1999-2024. Panel A presents the descriptive statistics of the firm pair-year level sample, based on the data on supply chain relationship ex-post duration. Panel B presents the regression results. In Panel B, columns 1-2 include industry pair × year fixed effects, columns 3-4 include industry pair × year, customer firm, and supplier firm fixed effects, and column 5-6 include industry pair × year and firm pair fixed effects. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Firm pair-year level descriptive characteristics

Variables	**N**	**Mean**	**SD**	**P25**	**P50**	**P75**
Dependent variables:						
Termination	7,127	0.098	0.297	0.000	0.000	0.000
Independent variables:						
Conf Word Ratio	7,127	0.027	0.026	0.008	0.020	0.036
Conf Word Decile	7,127	0.488	0.324	0.222	0.444	0.778
Supplier Violation (Raw $m)	7,127	6.368	39.454	0.000	0.000	0.000
Supplier Violation	7,127	2.963	5.682	0.000	0.000	0.000
Supplier Violation Alt	6,969	0.018	0.102	0.000	0.000	0.000
Supplier Import Comp	7,118	0.156	0.363	0.000	0.000	0.000
Supplier Fin Distress	6,096	0.106	0.308	0.000	0.000	0.000
Input Specificity	6,969	0.049	0.096	0.000	0.004	0.059
Material Supplier	6,969	0.601	0.490	0.000	1.000	1.000
R&D	7,127	0.076	0.153	0.000	0.018	0.084
Size	7,127	7.716	2.339	6.301	7.913	9.273
Age	7,127	15.858	6.665	11.000	16.000	20.000
Lev	7,127	0.280	0.240	0.111	0.261	0.385
ROA	7,127	-0.048	0.357	-0.016	0.028	0.075
Loss	7,127	0.285	0.451	0.000	0.000	1.000
Cash	7,127	0.196	0.238	0.010	0.094	0.313

Table 4 (continued)

Panel B: Baseline tests

Dependent variable:		*Termination*					
	Pr. Sign	(1)	(2)	(3)	(4)	(5)	(6)
Conf Word Ratio × Supplier Violation	-	-0.129**	-0.104**	-0.182**	-0.182**	-0.183**	-0.184**
		(-2.42)	(-2.02)	(-2.47)	(-2.49)	(-2.42)	(-2.44)
Conf Word Ratio		0.153	0.071	0.215	0.213	0.056	0.055
		(0.47)	(0.22)	(0.16)	(0.15)	(0.04)	(0.04)
Supplier Violation	+	0.004*	0.004*	0.008**	0.008***	0.008**	0.008***
		(1.71)	(1.71)	(2.42)	(2.64)	(2.42)	(2.64)
R&D			0.055		0.122**		0.119**
			(1.00)		(2.22)		(2.22)
Size			0.004		0.003		0.004
			(1.08)		(0.19)		(0.26)
Age			0.002		0.093		0.096
			(0.96)		(1.53)		(1.60)
Lev			-0.004		0.002		0.005
			(-0.19)		(0.04)		(0.09)
ROA			0.060***		0.091***		0.090***
			(2.66)		(3.37)		(3.39)
Loss			0.032*		0.062***		0.063***
			(1.90)		(3.43)		(3.53)
Cash			0.053		0.087		0.083
			(1.19)		(1.03)		(1.02)
Industry Pair × Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Customer Firm FE		No	No	Yes	Yes	No	No
Supplier Firm FE		No	No	Yes	Yes	No	No
Firm Pair FE		No	No	No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes	Yes	Yes
No. of observations		7,127	7,127	7,118	7,118	7,118	7,118
Adj. R-Squared		0.257	0.260	0.316	0.319	0.332	0.335

Table 5
Proprietary information sharing and supply chain relationship termination: Suppliers' alternative adverse events

This table presents the results examining the effect of potential proprietary information sharing on supply chain relationship termination likelihood in the case of suppliers' alternative adverse events. Panel A presents the results focusing on suppliers' import competition as suppliers' adverse events, and Panel B presents the results focusing on suppliers' financial distress as suppliers' adverse events. In both panels, the dependent variable is the indicator variable of supply chain relationship termination (*Termination*), and the sample is at firm pair-year level from years 1999-2024. Columns 1-2 include industry pair × year, customer firm, and supplier firm fixed effects, and column 3-4 include industry pair × year and firm pair fixed effects. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Suppliers' import competition

Dependent variable:		*Termination*			
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Import Comp	-	-1.460**	-1.522***	-1.522***	-1.584***
		(-2.47)	(-2.72)	(-2.71)	(-2.97)
Conf Word Ratio		-0.277	-0.285	-0.341	-0.348
		(-0.34)	(-0.35)	(-0.43)	(-0.44)
Supplier Import Comp	+	0.255**	0.259**	0.123***	0.128***
		(2.01)	(2.10)	(2.95)	(3.20)
Controls		No	Yes	No	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		7,118	7,118	7,118	7,118
Adj. R-Squared		0.315	0.318	0.331	0.334

Panel B: Suppliers' financial distress

Dependent variable:		*Termination*			
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Fin Distress	-	-1.071*	-1.042*	-1.076**	-1.048**
		(-1.93)	(-1.95)	(-1.97)	(-2.00)
Conf Word Ratio		-0.429	-0.458	-0.474	-0.503
		(-0.58)	(-0.63)	(-0.66)	(-0.71)
Supplier Fin Distress	+	0.059*	0.057*	0.060**	0.058**
		(1.88)	(1.92)	(1.97)	(2.01)
Controls		No	Yes	No	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		5,733	5,733	5,733	5,733
Adj. R-Squared		0.296	0.301	0.318	0.322

Table 6
Proprietary information sharing and supply chain relationship termination: Robustness tests of baseline findings

This table presents the results of robustness tests of Table 6 baseline findings. Panel A uses the decile rank of the confidentiality provision intensity (*Conf Word Decile*) as an alternative measure of proprietary information sharing. Panel B employs alternative fixed effect structures, specifically, including industry pair × year and supply chain contract fixed effects in columns 1-2, and including industry pair × year, supply chain contract, and state pair × year fixed effects in columns 3-4. Panel C further controls for input specificity (*Input Specificity*) and supplier importance (*Material Supplier*) and their interaction terms with *Supplier Violation*. Panel D excludes supply chain relationships initiating or terminating during COVID-19 period (years 2021-2022). The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Alternative measure of proprietary information sharing based on decile rank

Dependent variable:		*Termination*			
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Decile × Supplier Violation	-	-0.011**	-0.011**	-0.011**	-0.011**
		(-2.42)	(-2.46)	(-2.36)	(-2.40)
Conf Word Decile		0.023	0.024	0.014	0.015
		(0.28)	(0.28)	(0.17)	(0.18)
Supplier Violation	+	0.007**	0.008**	0.007**	0.008**
		(2.31)	(2.56)	(2.31)	(2.56)
Controls		No	Yes	No	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		7,118	7,118	7,118	7,118
Adj. R-Squared		0.316	0.319	0.332	0.335

Panel B: Alternative fixed effect structures

Dependent variable:		*Termination*			
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Violation	-	-0.193**	-0.195**	-0.189**	-0.192**
		(-2.21)	(-2.26)	(-2.00)	(-2.06)
Supplier Violation	+	0.007**	0.008**	0.007***	0.007***
		(2.09)	(2.35)	(2.86)	(2.99)
Controls		No	Yes	No	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Contract FE		Yes	Yes	Yes	Yes
State Pair × Year FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		7,118	7,118	6,447	6,447
Adj. R-Squared		0.333	0.336	0.492	0.493

Table 6 (continued)

Panel C: Control for input specificity and supplier importance

Dependent variable:		*Termination*			
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Violation	-	-0.168**	-0.169**	-0.167**	-0.168**
		(-2.27)	(-2.28)	(-2.17)	(-2.18)
Conf Word Ratio		0.115	0.114	-0.059	-0.059
		(0.08)	(0.08)	(-0.04)	(-0.04)
Supplier Violation	+	0.009***	0.010***	0.009***	0.010***
		(3.48)	(3.61)	(3.48)	(3.62)
Input Specificity × Supplier Violation		-0.002*	-0.002	-0.002*	-0.002
		(-1.76)	(-1.39)	(-1.74)	(-1.36)
Input Specificity		-0.012	-0.013	-0.012	-0.014
		(-0.71)	(-0.79)	(-0.77)	(-0.86)
Material Supplier × Supplier Violation		-0.003**	-0.003*	-0.003**	-0.003*
		(-2.15)	(-1.96)	(-2.10)	(-1.92)
Material Supplier		-0.019	-0.019	-0.018	-0.019
		(-1.58)	(-1.64)	(-1.53)	(-1.58)
Controls		No	Yes	No	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		7,118	7,118	7,118	7,118
Adj. R-Squared		0.318	0.321	0.334	0.337

Panel D: Exclude supply chain relationships initiating or terminating during COVID-19 period

Dependent variable:		*Termination*			
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Violation	-	-0.191***	-0.192***	-0.195***	-0.196***
		(-2.65)	(-2.67)	(-2.63)	(-2.65)
Conf Word Ratio		0.213	0.217	0.113	0.115
		(0.15)	(0.15)	(0.08)	(0.08)
Supplier Violation	+	0.008***	0.009***	0.009***	0.009***
		(2.81)	(3.04)	(2.85)	(3.07)
Controls		No	Yes	No	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		6,902	6,902	6,902	6,902
Adj. R-Squared		0.327	0.329	0.343	0.345

Table 7
Two quasi-natural experiments that change the proprietary value of information shared with suppliers

This table presents the results examining the effect of two quasi-natural experiments that change the proprietary value of information shared with suppliers. Panel A presents the results examining the effect of the American Inventors Protection Act on supply chain relationship terminations, using a customer firm-year level sample from 1995-2005 (excluding 2000). Panel B presents the results examining the effect of the Leahy-Smith America Invents Act on supply chain relationship terminations, using a customer firm-year level sample from 2008-2018 (excluding 2013). In both panels, the dependent variable is the natural log of one plus the number of supply chain relationship terminations (*Termination Num*). Columns 1-2 include firm and year fixed effects, and column 3 includes firm and industry × year fixed effects. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: American Inventors Protection Act (AIPA)

Dependent variable:		*Termination Num*		
	Pr. Sign	(1)	(2)	(3)
Treat $_{AIPA}$ × *AIPA*	+	0.070***	0.071***	0.070***
		(2.86)	(2.94)	(2.72)
R&D			0.240*	0.221
			(1.78)	(1.54)
Size			0.047***	0.045***
			(4.99)	(4.37)
Age			0.010	0.009
			(0.19)	(0.16)
Lev			0.004	0.004
			(0.08)	(0.09)
ROA			-0.011	-0.009
			(-0.24)	(-0.18)
Loss			-0.007	-0.009
			(-0.42)	(-0.51)
Cash			-0.017	-0.004
			(-0.35)	(-0.08)
Year FE		Yes	Yes	No
Industry × Year FE		No	No	Yes
Firm FE		Yes	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes
No. of observations		4,812	4,812	4,719
Adj. R-Squared		0.326	0.330	0.321

Table 7 (continued)

Panel B: Leahy-Smith America Invents Act (AIA)

Dependent variable:		*Termination Num*		
	Pr. Sign	(1)	(2)	(3)
Treat $_{AIA}$ × *AIA*	-	-0.074***	-0.079***	-0.063***
		(-4.24)	(-4.46)	(-3.64)
R&D			0.148***	0.127***
			(3.94)	(3.48)
Size			0.071***	0.074***
			(6.91)	(7.42)
Age			0.047	0.094**
			(1.22)	(2.51)
Lev			0.059**	0.050**
			(2.45)	(2.18)
ROA			-0.022	-0.019
			(-1.31)	(-1.17)
Loss			0.003	-0.003
			(0.30)	(-0.31)
Cash			0.007	-0.014
			(0.23)	(-0.46)
Year FE		Yes	Yes	No
Industry × Year FE		No	No	Yes
Firm FE		Yes	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes
No. of observations		15,755	15,755	15,745
Adj. R-Squared		0.581	0.584	0.592

Table 8
Cross-sectional tests on proprietary information sharing and supply chain relationship termination

This table presents the cross-sectional test results examining the effect of potential proprietary information sharing on supply chain relationship termination likelihood in the case of suppliers' regulatory violations. Panel A presents the results partitioning the sample into two subsamples based on customer firm market competition (*Compustat HHI*). Panel B presents the results partitioning the sample into two subsamples based on customer firm rivals' innovation intensity (*Ind R&D Intensity*). Panel C presents the results partitioning the sample into two subsamples based on the existence of other information sharing channels: common owners and directors (*Common Owner/Director*). In all panels, the dependent variable is the indicator variable of supply chain relationship termination (*Termination*), and the sample is at firm pair-year level from years 1999-2024. Columns 1-2 include industry pair × year, customer firm, and supplier firm fixed effects, and column 3-4 include industry pair × year and firm pair fixed effects. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Customer firm market competition

Dependent variable:		*Termination*			
Partition variable:		*Compustat HHI*			
Subsample:		Low	High	Low	High
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Violation	-,0,-,0	-0.388***	0.002	-0.414***	0.003
		(-3.51)	(0.03)	(-3.64)	(0.05)
p-value for difference in coefficients		<0.01		<0.01	
Conf Word Ratio		Yes	Yes	Yes	Yes
Supplier Violation		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		3,536	3,505	3,529	3,498
Adj. R-Squared		0.355	0.354	0.364	0.380

Panel B: Customer firm rivals' innovation intensity

Dependent variable:		*Termination*			
Partition variable:		*Ind R&D Intensity*			
Subsample:		High	Low	High	Low
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Violation	-,0,-,0	-0.366***	0.007	-0.396***	0.014
		(-3.55)	(0.10)	(-3.76)	(0.19)
p-value for difference in coefficients		<0.01		<0.01	
Conf Word Ratio		Yes	Yes	Yes	Yes
Supplier Violation		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		3,631	3,427	3,622	3,426
Adj. R-Squared		0.342	0.308	0.360	0.336

Table 8 (continued)

Panel C: Existence of other information sharing channels: Common owners and directors

Dependent variable:		*Termination*			
Partition variable:		*Common Owner/Director*			
Subsample:		No	Yes	No	Yes
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Violation	-,0,-,0	-0.241***	-0.024	-0.253***	-0.024
		(-2.84)	(-0.28)	(-2.93)	(-0.28)
p-value for difference in coefficients		0.04		0.04	
Conf Word Ratio		Yes	Yes	Yes	Yes
Supplier Violation		Yes	Yes	Yes	Yes
Controls		Yes	Yes	Yes	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		5610	1396	5610	1396
Adj. R-Squared		0.326	0.427	0.343	0.450

Online Appendix for

"Information Hostage: Inter-Firm Proprietary Information Sharing and Supply Chain Lock-In"

OA.1 Validating the Proxy for Customer-to-Supplier Proprietary Information Sharing

In this section, I detail additional tests validating confidentiality provision intensity as a measure of customer-to-supplier proprietary information sharing. Specifically, I examine whether suppliers entering into high-confidentiality-intensity contracts exhibit greater managerial learning relative to those in low-intensity contracts. Given the economic interdependence of supply chain partners (e.g., Houston et al., 2016; Cen et al., 2017; Gong and Luo, 2018), customers' proprietary information, though shared primarily for supply chain coordination, can also broaden suppliers' information sets and inform corporate decision-making. Accordingly, if confidentiality intensity reflects the extent of such information exchange, suppliers in higher-intensity contracts should exhibit greater managerial learning. Observing such a pattern would support construct validity, as suppliers' learning should not systematically differ across contracts if confidentiality intensity were unrelated to the extent of customer-to-supplier information sharing.

I focus on three dimensions of suppliers' managerial learning: (i) information environment quality, (ii) investment quality, and (iii) innovation quality, given that a substantial portion of contracts involve R&D-related information sharing.

OA.1.1 Proprietary Information Sharing and Information Environment Quality

To test whether customer-to-supplier proprietary information sharing improves suppliers' information environment, I implement a stacked difference-in-differences design that compares changes in information environment quality for suppliers entering into high- versus low-confidentiality-intensity contracts. High-intensity contracts are defined as those in the top quartile of confidentiality provision intensity, with all others designated as low-intensity.[12] I define treatment suppliers as those entering at least one high-intensity contract during the sample period (*Treat* = 1), while control suppliers appear only in low-intensity contracts (*Treat* = 0). This setup mitigates concerns about endogenous selection into material supply chain contracting, as both treatment and control groups are suppliers in at least one publicly disclosed, material contract. I then construct a stacked cohort-supplier-year panel, where each contract start year forms a separate cohort. Within each cohort, treatment suppliers are matched to control suppliers entering into low-intensity contracts in the same year (Goodman-Bacon, 2021; Baker et al., 2022; Barrios, 2024),

[12] In untabulated robustness tests, my inferences remain consistent when using the top tercile or median to classify high- versus low-confidentiality-intensity contracts.

ensuring contemporaneous contract entry and mitigating concerns about endogenous timing of contracting. Given the median five-year contract duration in my sample and prior research (e.g., Costello, 2013), I use an eleven-year event window spanning five years before and after contract initiation. I estimate the following OLS regression:

$$Y_{i,t,c} = \beta_0 + \beta_1 Treat_{i,c} \times Post_{t,c} + \sum \beta_i \, Controls_{i,t,c} + FEs + \varepsilon_{i,t,c} \quad (2)$$

where *i* indexes supplier firms, *t* fiscal years, and *c* cohorts. The dependent variable *Y* represents four commonly used proxies for information environment quality: earnings announcement speed, the likelihood of issuing management earnings forecasts, forecast accuracy, and forecast precision (e.g., Dorantes et al., 2013; Gallemore and Labro, 2015; Ittner and Michels, 2017).

The first proxy, earnings announcement speed (*EA Speed*), is measured as the number of days between fiscal year-end and the annual earnings announcement. If proprietary information acquired through supply chain relationships enriches suppliers' information sets, it potentially facilitates the information integration within the firm and shortens the time required to prepare and release financial statements.

Disclosure theory posits that managers with richer information sets are more likely to provide voluntary disclosures to reduce agency conflicts or signal competence (e.g., Diamond, 1985; Trueman, 1986; Verrecchia, 1990). Accordingly, I examine three forecast-based proxies: (i) *Mgmt Forecast Issue*, an indicator for whether the supplier issues an annual EPS forecast; (ii) *Mgmt Forecast Error*, the absolute difference between the last available supplier-issued EPS forecast (midpoint if a range) and actual EPS, scaled by actual EPS (e.g., Bradshaw et al., 2012; Shroff et al., 2013); and (iii) *Mgmt Forecast Width*, the forecast range scaled by the midpoint, with point forecasts coded as zero. Following prior research (e.g., Rogers and Stocken, 2005; Goodman et al., 2014), I focus on annual forecasts, which are less subject to short-term manipulation and better reflect firms' underlying information environment.

Additionally, I control for firm characteristics including R&D intensity (*R&D*), size (*Size*), age (*Age*), financial leverage (*Lev*), return on assets (*ROA*), loss occurrence (*Loss*), and cash holdings (*Cash*). The regressions include cohort × firm fixed effects and cohort × year fixed effects to absorb time-invariant firm factors and general time trends. In alternative specifications, I further include cohort × industry × year fixed effects to account for industry-level time-variant factors.

Table OA1 Panel A presents the summary statistics for the stacked cohort-supplier-year level sample during years 1994-2024.[13] Panels B-C report the estimates from Eq. (2), with sample sizes varying with the availability of outcome variables. Panel B columns 1-3 and 4-6 use *EA Speed* and *Mgmt Forecast Issue* as dependent variables, respectively. Panel C columns 1-3 and 4-6 use *Mgmt Forecast Error* and *Mgmt Forecast Width* as dependent variables. The results show that treatment suppliers announce earnings faster, are more likely to issue management forecasts, and issue forecasts that are more accurate and precise after contract initiation, relative to controls.

To support the parallel trends assumption (Angrist and Pischke, 2008), I conduct an event-time analysis to examine the dynamic effect of entering into high-confidentiality-intensity contracts, relative to low-intensity contracts, by estimating the following OLS model:

$$\begin{aligned} Y_{i,t,c} = \beta_0 &+ \beta_1 Treat_{i,c} \times Year\ t-3_{t,c} + \beta_2 Treat_{i,c} \times Year\ t-2_{t,c} \\ &+ \beta_3 Treat_{i,c} \times Year\ t-1_{t,c} + \beta_4 Treat_{i,c} \times Year\ t_{t,c} \\ &+ \beta_5 Treat_{i,c} \times Year\ t+1_{t,c} + \beta_6 Treat_{i,c} \times Year\ t+2_{t,c} \\ &+ \beta_7 Treat_{i,c} \times Year\ t+3_{t,c} + \beta_8 Treat_{i,c} \times Year\ t+4_{t,c} \\ &+ \sum \beta_i\ Controls_{i,t,c} + FEs + \varepsilon_{i,t,c} \end{aligned} \quad (3)$$

where *Year t-3* to *Year t+3* are indicator variables for event years *t-3* through *t+3*, *Year t-4* is an indicator for event years *t-5 to t-4*, and *Year t+4* is an indicator for event years *t+4 to t+5*. *Year t-4* is excluded because it serves as the benchmark period. Figure OA1 plots the dynamic effects, showing no pre-trends in information environment quality between treatment and control suppliers. After contract initiation, treatment suppliers exhibit significant improvements relative to controls. Overall, Table OA1 and Figure OA1 indicate that suppliers in higher-intensity contracts experience enhanced information environments.

OA.1.2 Proprietary Information Sharing and Investment Quality

To assess investment quality, I employ two sets of measures. First, I examine whether entering into high-confidentiality-intensity contracts improves the investment efficiency of underinvesting and overinvesting suppliers, using the following OLS equation:

[13] The stacked sample begins in 1994, five years prior to the earliest contract start year (1999), and ends in 2024 due to the availability of annual firm fundamental data.

$$Investment_{i,t,c} = \beta_0 + \beta_1 Treat_{i,c} \times Post_{t,c} \times Over\ Firm_{i,t,c} + \beta_2 Treat_{i,c} \times Post_{t,c} + \beta_3 Treat_{i,c} \times Over\ Firm_{i,t,c} + \beta_4 Post_{t,c} \times Over\ Firm_{i,t,c} + \beta_5 Over\ Firm_{i,t,c} + \sum \beta_i\ Controls_{i,t,c} + FEs + \varepsilon_{i,t,c} \quad (4)$$

where the dependent variable, *Investment*, is the total investment defined as the sum of R&D expense, acquisition expenditure, and capital expenditure, less the proceeds from sales of property, plants, and equipment, scaled by total assets. Following Cheng et al. (2013), I use a variable *Over Firm* to capture firms' ex-ante likelihood of over- and underinvestment. Specifically, I rank firms into two decile ranks according to its cash balances and (negative) leverage by industry and year. The average of these two decile ranks for each firm is scaled to the range of zero and one. Thus, firms that have larger (or smaller) cash holdings and lower (or higher) leverage compared with their industry peers are considered to be prone to overinvestment (or underinvestment).

Table OA2 Panel A presents estimates of Eq. (4). Across all specifications, the coefficients on *Treat* × *Post* are significantly positive, indicating that, following contract initiation, treatment suppliers prone to underinvestment (i.e., *Over Firm* → 0) increase investment relative to their control counterparts. The sum of the coefficients on *Treat* × *Post* × *Over Firm* and *Treat* × *Post* is significantly negative, suggesting that overinvesting treatment suppliers (i.e., *Over Firm* → 1) cut back investment relative to overinvesting control suppliers after contract initiation. Dynamic effect estimates in Figure OA2 Panels A-B suggest no pre-trend violations. Overall, the evidence indicates that both over- and underinvesting treatment suppliers improve investment efficiency after contract initiation, relative to control suppliers.[14]

Second, to evaluate the quality of acquisitions, a key form of corporate investment, I examine acquisition announcement returns (e.g., Asquith et al., 1983; Goodman et al., 2014). The underlying premise is that capital markets efficiently incorporate deal quality into prices, such that stock price reactions around announcements reflect changes in acquirers' fundamental value. I compute acquisition announcement returns (*Acquisition CAR [-1,+1]*) as the three-day cumulative abnormal return of the acquirer centered on the announcement date, using the Fama-French three-

[14] In untabulated analyses, following Biddle et al. (2009), I measure investment efficiency using the absolute value of residuals from a firm-level regression of future investment on current-year sales growth (*Invest Inefficiency*) (see Appendix A for details). Smaller residuals (i.e., a lower value of *Invest Inefficiency*) indicates that investment decisions are more closely aligned with growth opportunities, and thus reflect higher efficiency. I find consistent evidence that treatment suppliers improve investment efficiency relative to control suppliers, following contract initiation.

factor model.[15] Since not all suppliers in my sample undertake acquisitions both before and after contract initiation, I modify Eq. (2) by including cohort × industry fixed effects in place of cohort × firm fixed effects.[16] The estimates in Table OA2 Panel B show that, after contract initiation, acquisitions by treatment suppliers elicit significantly more positive market reactions relative to those by control suppliers, supporting the prediction that access to customers' proprietary information improves suppliers' acquisition decisions. Figure OA2 Panel C supports the parallel trends assumption. Overall, the evidence in Table OA2 and Figure OA2 suggests that customer-to-supplier proprietary information sharing improves suppliers' capital allocation decisions and fosters more disciplined investment behavior.

OA.1.3 Proprietary Information Sharing and Innovation Quality

As R&D information is the most frequently referenced category of shared information in supply chain contracts (see Figure 2), I conjecture that another dimension of suppliers' managerial learning pertains to innovation. Specifically, R&D information shared by customers facilitates suppliers to make more effective R&D decisions and produce higher-quality innovation outputs. I measure innovation quality using the private economic value of patents (*Patent Value*), developed by Kogan et al. (2017), which is based on abnormal stock market reactions to patent grants. Table OA3 reports the results of estimating Eq. (2) with *Patent Value* as the dependent variable. Consistent with my conjecture, suppliers entering high-confidentiality-intensity contracts subsequently generate more valuable patents than control suppliers. Dynamic estimates in Figure OA3 further support the parallel trends assumption.

Taken together, the documented improvements in suppliers' information environments, investment efficiency, and innovation quality not only reinforce the construct validity of confidentiality provision intensity as a proxy for customer-to-supplier proprietary information sharing, but also highlight its broader economic benefits, which extend beyond the operational coordination traditionally emphasized in prior research.

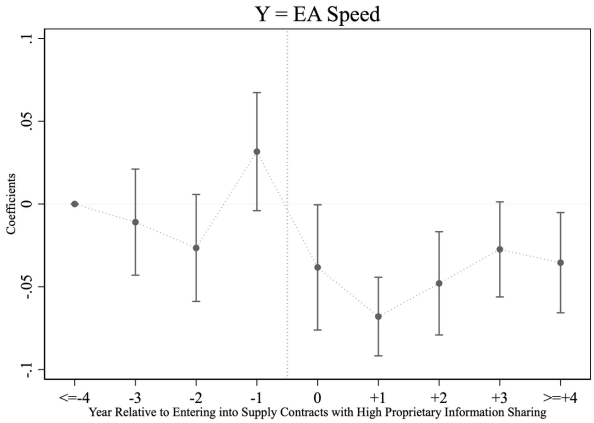
[15] In untabulated robustness tests, my inferences are consistent when using alternative models to compute abnormal returns, including the market-adjusted model, market model, and Fama-French four-factor model.

[16] Using firm fixed effects would restrict identification to within-firm variation, which substantially reduces the sample given that only a small fraction of firms conduct acquisitions both pre- and post-contract. This approach is consistent with prior studies (e.g., Huang and Kisgen, 2013; Dey and White, 2021).

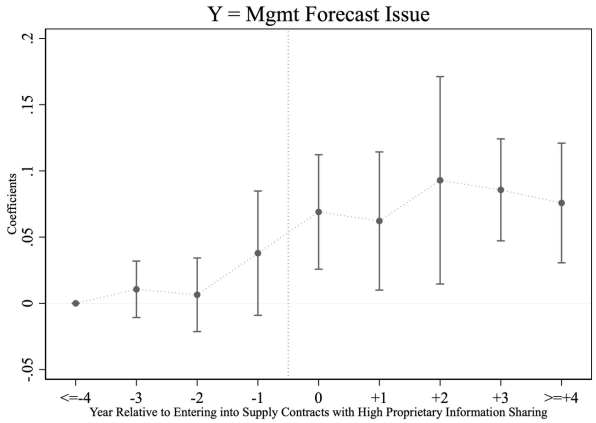
Figure OA1
Dynamic effect of proprietary information sharing on managerial learning: Information environment quality

The figure in Panel A (B, C, D) displays the effect of potential proprietary information sharing on supplier firms' information environment quality in event time, using *EA Speed* (*Mgmt Forecast Issue*, *Mgmt Forecast Error*, *Mgmt Forecast Width*) as the dependent variable. Formally, using a cohort-firm-year level sample, I estimate $Y_{i,t,c} = \alpha + \sum_{n=t-3}^{t+4} \beta_{k1}\ Treat_{i,c} \times Year\ n_{t,c} + \beta_k Controls + \delta_{i\times c} + \gamma_{ind\times t\times c} + \epsilon_{i,t,c}$, where $\delta_{i\times c}$ and $\gamma_{ind\times t\times c}$ represent cohort × firm and cohort × industry × fiscal year fixed effects, respectively. In each panel, *Year t-3* to *Year t+3* are indicator variables for event years *t-3* through *t+3*, *Year t-4* is an indicator variable for event years *t-5 to t-4*, and *Year t+4* is an indicator variable for event years *t+4 to t+5*. Each point estimate is accompanied by a 90% confidence interval calculated based on standard errors clustered by industry. Note that *Year t-4* has a coefficient of zero and no confidence interval because it serves as the benchmark period. All variables are defined in Appendix A.

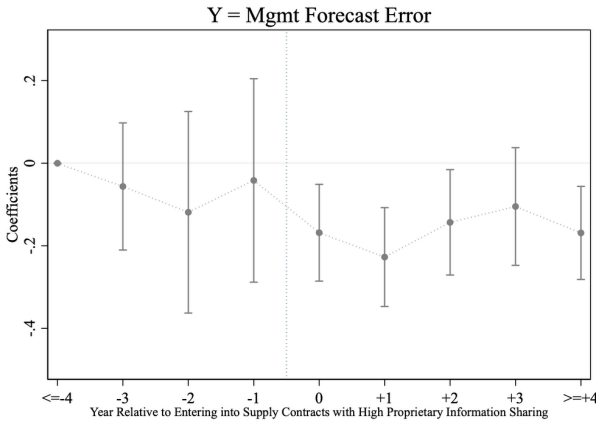
Panel A: Earnings announcement speed



Panel B: Management earnings forecast likelihood



Panel C: Management earnings forecast error



Panel D: Management earnings forecast width

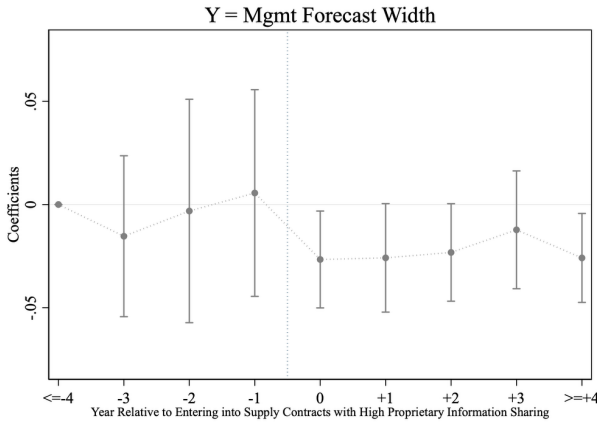
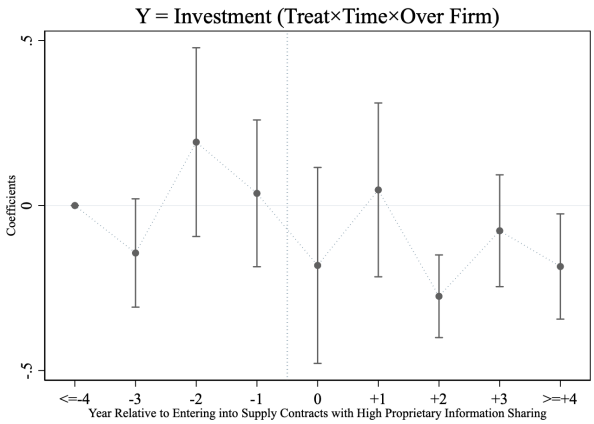


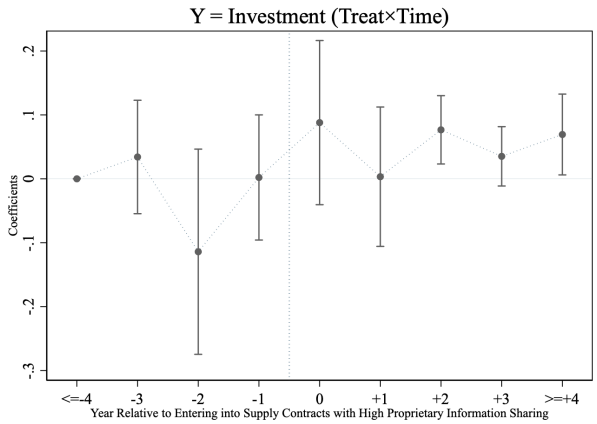
Figure OA2
Dynamic effect of proprietary information sharing on managerial learning: Investment quality

The figure in Panel A (B, C) displays the effect of potential proprietary information sharing on supplier firms' investment quality in event time. Formally, in Panels A-B, using a cohort-firm-year level sample, I estimate $Investment_{i,t,c} = \alpha + \sum_{n=t-3}^{t+4} \beta_{k1}\ Treat_{i,c} \times Year\ n_{t,c} \times Over\ Firm_{i,t,c} + \sum_{n=-3}^{4} \beta_{k2}\ Treat_{i,c} \times Year\ n_{t,c} + \sum_{n=-3}^{4} \beta_{k3}\ Year\ n_{t,c} \times Over\ Firm_{i,t,c} + Treat_{i,c} \times Over\ Firm_{i,t,c} + Over\ Firm_{i,t,c} + \beta_k Controls + \delta_{i\times c} + \gamma_{ind\times t\times c} + \epsilon_{i,t,c}$, where $\delta_{i\times c}$ and $\gamma_{ind\times t\times c}$ represent cohort × firm and cohort × industry × fiscal year fixed effects, respectively. Panel A plots the coefficients on *Treat* × *Year* × *Over Firm*, while Panel B plots the coefficients on *Treat* × *Year*. In Panel C, using a cohort-deal level sample, I estimate $Acquisition\ CAR\ [-1,+1]_{d,t,c} = \alpha + \sum_{n=t-3}^{t+4} \beta_{k1}\ Treat_{d,c} \times Year\ n_{t,c} + \beta_k Controls + \gamma_{ind\times t\times c} + \epsilon_{i,d,c}$, where $\gamma_{ind\times t\times c}$ represents cohort × industry × fiscal year fixed effects. In each panel, *Year t-3* to *Year t+3* are indicator variables for event years *t-3* through *t+3*, *Year t-4* is an indicator variable for event years *t-5 to t-4*, and *Year t+4* is an indicator variable for event years *t+4 to t+5*. Each point estimate is accompanied by a 90% confidence interval calculated based on standard errors clustered by industry. Note that *Year t-4* has a coefficient of zero and no confidence interval because it serves as the benchmark period. All variables are defined in Appendix A.

Panel A: Overinvestment



Panel B: Underinvestment



Panel C: M&A quality

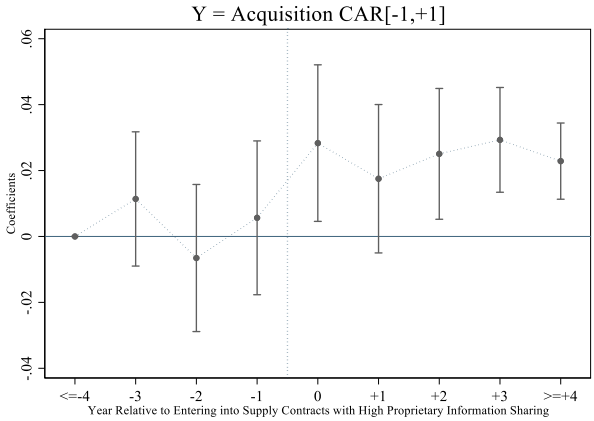


Figure OA3
Dynamic effect of proprietary information sharing on managerial learning: Innovation quality

The figure displays the effect of potential proprietary information sharing on supplier firms' innovation quality in event time. Formally, using a cohort-firm-year level sample, I estimate $Patent\ Value_{i,t,c} = \alpha + \sum_{n=t-3}^{t+4} \beta_{k1}\ Treat_{i,c} \times Year\ n_{t,c} + \beta_k Controls\ + \delta_{i\times c} + \gamma_{ind\times t\times c} + \epsilon_{i,t,c}$, where $\delta_{i\times c}$ and $\gamma_{ind\times t\times c}$ represent cohort × firm and cohort × industry × fiscal year fixed effects, respectively. *Year t-3* to *Year t+3* are indicator variables for event years *t-3* through *t+3*, *Year t-4* is an indicator variable for event years *t-5 to t-4*, and *Year t+4* is an indicator variable for event years *t+4 to t+5*. Each point estimate is accompanied by a 90% confidence interval calculated based on standard errors clustered by industry. Note that *Year t-4* has a coefficient of zero and no confidence interval because it serves as the benchmark period. All variables are defined in Appendix A.

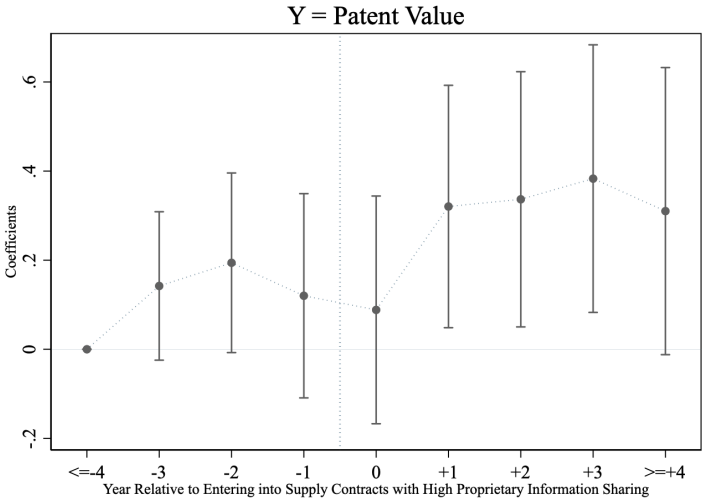


Table OA1
Proprietary information sharing and managerial learning: Information environment quality

This table presents the stacked difference-in-differences design results examining the effect of potential proprietary information sharing on supplier firms' managerial learning, focusing on information environment quality. Panel A presents the descriptive statistics of the stacked cohort-firm-year level sample from years 1994-2024. Panels B-C present the results examining the effect of potential proprietary information sharing on supplier firms' information environment quality, measured by earnings announcement speed (*EA Speed*) and management earnings forecast likelihood (*Mgmt Forecast Issue*) in Panel B, and management earnings forecast error (*Mgmt Forecast Error*) and forecast width (*Mgmt Forecast Width*) in Panel C. In Panels B-C, columns 1-2 and 4-5 include cohort × year and cohort × firm fixed effects, and columns 3 and 6 include cohort × industry × year and cohort × firm fixed effects. The sample size varies with the availability of dependent variables. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Cohort-firm-year level descriptive statistics

Variables	N	Mean	SD	P25	P50	P75
Dependent variables:						
EA Speed (Raw)	37,355	58.091	31.628	36.000	53.000	73.000
EA Speed	37,355	3.936	0.500	3.584	3.970	4.290
Mgmt Forecast Issue	28,290	0.269	0.443	0.000	0.000	1.000
Mgmt Forecast Error	6,575	0.175	0.555	0.014	0.035	0.091
Mgmt Forecast Width	6,575	0.046	0.069	0.008	0.026	0.055
Investment	21,394	0.228	0.323	0.061	0.132	0.256
Acquisition CAR [-1,+1]	5,564	0.003	0.086	-0.030	-0.001	0.031
Patent Value (Raw $m)	23,952	1,250.082	4,676.667	0.000	1.983	85.603
Patent Value	23,952	2.502	3.046	0.000	1.093	4.461
Independent variables:						
Treat × Post	37,355	0.030	0.171	0.000	0.000	0.000
Treat	37,355	0.053	0.225	0.000	0.000	0.000
Post	37,355	0.545	0.498	0.000	1.000	1.000
R&D	37,355	0.111	0.234	0.000	0.021	0.115
Size	37,355	6.140	2.874	4.014	6.263	8.263
Age	37,355	12.747	6.400	8.000	12.000	17.000
Lev	37,355	0.281	0.379	0.037	0.213	0.368
ROA	37,355	-0.276	1.082	-0.181	0.017	0.068
Loss	37,355	0.433	0.496	0.000	0.000	1.000
Cash	37,355	0.232	0.264	0.028	0.123	0.347

Table OA1 (continued)

Panel B: Earnings announcement speed and earnings forecast likelihood

Dependent variable:		*EA Speed*			*Mgmt Forecast Issue*		
	Pr. Sign	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	-	-0.055***	-0.049***	-0.044***	0.053***	0.050**	0.057**
		(-4.24)	(-3.21)	(-2.89)	(2.80)	(2.40)	(2.59)
R&D			-0.012	-0.022*		0.008	-0.014
			(-0.79)	(-1.85)		(0.31)	(-0.47)
Size			-0.069***	-0.064***		0.053***	0.048***
			(-7.01)	(-5.44)		(5.92)	(4.76)
Age			-0.004	-0.002		0.067	-0.013
			(-0.53)	(-0.09)		(1.50)	(-0.27)
Lev			0.016	0.030**		-0.058	-0.059
			(1.30)	(2.31)		(-1.06)	(-0.94)
ROA			0.011*	0.012**		-0.046***	-0.058***
			(1.84)	(2.27)		(-4.12)	(-3.52)
Loss			0.110***	0.102***		-0.089***	-0.080***
			(10.60)	(9.93)		(-5.02)	(-3.73)
Cash			-0.104***	-0.079***		-0.030	-0.032
			(-3.04)	(-2.84)		(-0.96)	(-1.15)
Cohort × Year FE		Yes	Yes	No	Yes	Yes	No
Cohort × Firm FE		Yes	Yes	Yes	Yes	Yes	Yes
Cohort × Industry × Year FE		No	No	Yes	No	No	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes	Yes	Yes
No. of observations		37,355	37,355	34,624	28,290	28,290	25,596
Adj. R-Squared		0.723	0.735	0.730	0.569	0.578	0.568

Panel C: Management earnings forecast error and width

Dependent variable:		*Mgmt Forecast Error*			*Mgmt Forecast Width*		
	Pr. Sign	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	-	-0.101***	-0.102**	-0.132**	-0.021***	-0.016***	-0.015**
		(-2.82)	(-2.26)	(-2.60)	(-4.58)	(-3.95)	(-2.62)
R&D			-0.437	-0.464		-0.160***	-0.154***
			(-0.82)	(-0.95)		(-5.54)	(-4.43)
Size			-0.065*	-0.051*		-0.032***	-0.026***
			(-1.95)	(-1.83)		(-4.31)	(-3.76)
Age			-0.061	0.063		-0.015	-0.014
			(-0.90)	(0.51)		(-0.94)	(-0.46)
Lev			0.620**	0.486*		0.092*	0.066*
			(2.19)	(1.81)		(2.00)	(1.76)
ROA			-0.707	-0.594		-0.043	-0.082**
			(-1.14)	(-1.17)		(-1.31)	(-2.83)
Loss			-0.102	-0.092		0.013	0.006
			(-1.34)	(-0.89)		(1.15)	(0.58)
Cash			-0.085	0.087		-0.095***	-0.130***
			(-0.40)	(0.75)		(-3.36)	(-4.06)
Cohort × Year FE		Yes	Yes	No	Yes	Yes	No
Cohort × Firm FE		Yes	Yes	Yes	Yes	Yes	Yes
Cohort × Industry × Year FE		No	No	Yes	No	No	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes	Yes	Yes
No. of observations		6,575	6,575	4,829	6,575	6,575	4,829
Adj. R-Squared		0.255	0.268	0.279	0.385	0.424	0.399

Table OA2
Proprietary information sharing and managerial learning: Investment quality

This table presents the stacked difference-in-differences design results examining the effect of potential proprietary information sharing on supplier firms' managerial learning, focusing on investment quality. Panel A presents the results examining the effect of potential proprietary information sharing on supplier firms' overinvestment and underinvestment, following Cheng et al. (2013). Panel B presents the results examining the effect of potential proprietary information sharing on supplier firms' M&A quality, measured by acquisition announcement returns (*Acquisition CAR [-1,+1]*). In Panel A where the sample consists of cohort-firm-year level observations from 1994-2024, columns 1-2 include cohort × year and cohort × firm fixed effects, and column 3 includes cohort × industry × year and cohort × firm fixed effects. In Panel B where the sample consists of cohort-acquisition level observations from 1994-2024, columns 1-2 include cohort × year and cohort × industry fixed effects, and column 3 includes cohort × industry × year fixed effects. The sample size varies with the availability of dependent variables. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Overinvestment and underinvestment

Dependent variable:		*Investment*		
	Pr. Sign	(1)	(2)	(3)
Treat × Post × Over Firm (1)	-	-0.135**	-0.185**	-0.185**
		(-2.36)	(-2.67)	(-2.41)
Treat × Post (2)	+	0.067*	0.085***	0.087***
		(2.02)	(2.80)	(3.14)
Treat × Over Firm		0.147	0.191**	0.190**
		(1.32)	(2.65)	(2.37)
Post × Over Firm		0.015	0.051	0.051
		(0.51)	(1.66)	(1.41)
Over Firm		0.130***	0.000	-0.028
		(4.23)	(0.01)	(-0.50)
R&D			0.065	0.100*
			(1.25)	(1.98)
Size			-0.071***	-0.071***
			(-4.81)	(-5.36)
Age			-0.036	-0.030
			(-1.41)	(-0.97)
Lev			-0.040*	-0.083***
			(-1.75)	(-5.64)
ROA			-0.013	-0.013
			(-1.28)	(-1.38)
Loss			-0.007	-0.007
			(-0.65)	(-0.54)
Cash			0.120***	0.114**
			(3.49)	(2.06)
(1) + (2)	-	-0.068*	-0.100**	-0.098*
		(1.76)	(-2.20)	(-1.77)
Cohort × Year FE		Yes	Yes	No
Cohort × Firm FE		Yes	Yes	Yes
Cohort × Industry × Year FE		No	No	Yes
S.E. clustered by industry		Yes	Yes	Yes
No. of observations		21,394	21,394	18,790
Adj. R-Squared		0.411	0.438	0.291

Table OA2 (continued)

Panel B: M&A quality

Dependent variable:		*Acquisition CAR [-1,+1]*		
	Pr. Sign	(1)	(2)	(3)
Treat × Post	+	0.020**	0.021**	0.025**
		(2.41)	(2.06)	(2.27)
Treat		-0.017*	-0.015	-0.022**
		(-1.83)	(-1.57)	(-2.08)
R&D			0.065	0.070
			(1.14)	(1.20)
Size			-0.003*	-0.002
			(-1.79)	(-1.11)
Age			-0.001	-0.000
			(-1.56)	(-0.83)
Lev			0.037	0.043
			(1.27)	(1.67)
ROA			0.031	0.047
			(0.86)	(1.28)
Loss			0.007	0.008
			(0.49)	(0.54)
Cash			0.025	0.047
			(0.68)	(1.17)
Cohort × Year FE		Yes	Yes	No
Cohort × Industry FE		Yes	Yes	No
Cohort × Industry × Year FE		No	No	Yes
S.E. clustered by industry		Yes	Yes	Yes
No. of observations		5,564	5,564	4,737
Adj. R-Squared		-0.012	0.007	0.059

Table OA3
Proprietary information sharing and managerial learning: Innovation quality

This table presents the stacked difference-in-differences design results examining the effect of potential proprietary information sharing on supplier firms' managerial learning, focusing on innovation quality measured by patent value (*Patent Value*). The sample consists of cohort-firm-year level observations from 1994-2024. Columns 1-2 include cohort × year and cohort × firm fixed effects, and column 3 includes cohort × industry × year and cohort × firm fixed effects. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dependent variable:		*Patent Value*		
	Pr. Sign	(1)	(2)	(3)
Treat × Post	+	0.186*	0.174*	0.235**
		(1.86)	(1.92)	(2.49)
R&D			0.483***	0.570***
			(4.07)	(3.85)
Size			0.311***	0.332***
			(3.92)	(3.30)
Age			0.676**	0.631
			(2.28)	(0.99)
Lev			-0.211***	-0.172**
			(-4.46)	(-2.52)
ROA			-0.038	-0.038
			(-0.49)	(-0.40)
Loss			-0.129*	-0.075
			(-1.91)	(-1.33)
Cash			0.185	0.160
			(1.03)	(0.91)
Cohort × Year FE		Yes	Yes	No
Cohort × Firm FE		Yes	Yes	Yes
Cohort × Industry × Year FE		No	No	Yes
S.E. clustered by industry		Yes	Yes	Yes
No. of observations		23,952	23,952	21,540
Adj. R-Squared		0.879	0.883	0.892

Table OA4
Proprietary information sharing and supply chain relationship ex-post duration

This table presents the results examining the association between potential proprietary information sharing and supply chain relationship ex-post duration. Panel A presents the descriptive statistics of the sample of supply chain contracts during 1999 to 2024, with available data on supply chain relationship ex-post duration. Panel B presents the regression results, using *Duration Ex-Post* as the dependent variable. In Panel B, columns 1, 3, 5, and 7 include year and both supplier industry and customer industry fixed effects, and columns 2, 4, 6, and 8 include year and industry pair fixed effects. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by both industries. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Contract-level descriptive characteristics

Variables	N	Mean	SD	P25	P50	P75
Dependent variables:						
Duration Ex-Post (Raw)	961	7.611	6.163	3.000	6.000	10.000
Duration Ex-Post	961	1.914	0.704	1.386	1.946	2.398
Independent variables:						
Conf Word Ratio	961	0.029	0.030	0.005	0.021	0.043
R&D Cus	961	0.111	0.200	0.003	0.041	0.115
R&D Sup	961	0.090	0.154	0.000	0.025	0.103
Trade Secret Cus	961	0.987	0.967	0.000	1.099	1.792
Trade Secret Sup	961	1.095	1.003	0.000	1.099	1.946
Patent Cus	961	2.584	2.840	0.000	1.792	4.913
Patent Sup	961	2.112	2.486	0.000	1.099	3.892
Same Industry	961	0.560	0.497	0.000	1.000	1.000
Customer Power	961	0.552	0.498	0.000	1.000	1.000
Intangible Cus	961	0.078	0.119	0.000	0.020	0.115
Intangible Sup	961	0.052	0.086	0.000	0.012	0.062
ROA Cus	961	-0.097	0.529	-0.107	0.039	0.123
ROA Sup	961	-0.049	0.629	-0.054	0.040	0.109
Leader Cus	961	0.148	0.355	0.000	0.000	0.000
Leader Sup	961	0.096	0.294	0.000	0.000	0.000
Size Cus	961	7.264	2.907	4.677	7.473	9.760
Size Sup	961	6.444	2.701	4.204	6.425	8.687
Age Cus	961	12.179	6.779	6.000	13.000	17.000
Age Sup	961	12.434	7.280	6.000	13.000	18.000
Lev Cus	961	0.238	0.234	0.074	0.169	0.334
Lev Sup	961	0.230	0.213	0.070	0.175	0.355
Total Word Num Ln	961	9.066	0.869	8.647	9.189	9.643
Duration Ex-Ante (Raw)	961	5.349	4.089	3.000	5.000	5.000
Duration Ex-Ante	961	1.436	0.719	1.099	1.609	1.609
Renewal	961	0.554	0.497	0.000	1.000	1.000
Demand Forecast	961	0.602	0.490	0.000	1.000	1.000

Table OA4 (continued)

Panel B: Contract-level regression results

Dependent variable:		*Duration Ex-Post*							
	Pr. Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conf Word Ratio	+	3.171***	2.945***	3.517***	3.418***	2.977***	2.763***	3.331***	3.182***
		(3.61)	(3.59)	(3.75)	(3.69)	(3.36)	(3.31)	(3.66)	(3.50)
R&D Cus		0.369	0.501					0.320	0.462*
		(1.10)	(1.53)					(1.11)	(1.72)
R&D Sup		-0.449***	-0.574***					-0.342	-0.438**
		(-2.83)	(-3.45)					(-1.35)	(-2.20)
Trade Secret Cus				-0.034	-0.074*			-0.025	-0.066*
				(-0.71)	(-1.68)			(-0.59)	(-1.70)
Trade Secret Sup				-0.059	-0.067*			-0.046	-0.052
				(-1.65)	(-1.84)			(-1.40)	(-1.61)
Patent Cus						0.024	0.028	0.008	0.003
						(0.97)	(1.13)	(0.46)	(0.18)
Patent Sup						-0.017	-0.021	-0.007	-0.012
						(-0.42)	(-0.48)	(-0.17)	(-0.28)
Controls in Table 3 Determinant Tests		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier Industry FE		Yes	No	Yes	No	Yes	No	Yes	No
Customer Industry FE		Yes	No	Yes	No	Yes	No	Yes	No
Industry Pair FE		No	Yes	No	Yes	No	Yes	No	Yes
S.E. clustered by both industries		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations		961	954	961	954	961	954	961	954
Adj. R-Squared		0.406	0.431	0.404	0.428	0.401	0.423	0.406	0.433

Table OA5
Additional robustness tests on proprietary information sharing and supply chain relationship termination: Alternative measures of suppliers' adverse events

This table presents the additional robustness test results examining the effect of potential proprietary information sharing on supply chain relationship termination likelihood in the case of suppliers' adverse events, using alternative measures of suppliers' adverse events. The dependent variable is the indicator variable of supply chain relationship termination (*Termination*), and the sample is at firm pair-year level from years 1999-2024. Panel A uses the regulatory violation penalty scaled by total assets (*Supplier Violation Alt*) as an alternative measure of suppliers' regulatory violations. Panel B uses the Ohlson's O-score (*Supplier Fin Distress Alt*) as an alternative measure of suppliers' financial distress. In each panel, columns 1-2 include industry pair × year, customer firm, and supplier firm fixed effects, and column 3-4 include industry pair × year and firm pair fixed effects. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by industry. All variables are defined in Appendix A. *, **, *** indicate statistics significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Alternative measure of suppliers' regulatory violations based on scaled regulatory violation penalty

Dependent variable:		*Termination*			
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Violation Alt	-	-16.492***	-16.379***	-16.562***	-16.441***
		(-3.18)	(-3.16)	(-3.28)	(-3.25)
Conf Word Ratio		-0.181	-0.183	-0.304	-0.308
		(-0.15)	(-0.15)	(-0.26)	(-0.26)
Supplier Violation Alt	+	0.577***	0.577***	0.583***	0.584***
		(3.51)	(3.51)	(3.65)	(3.65)
Controls		No	Yes	No	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		6,969	6,969	6,969	6,969
Adj. R-Squared		0.325	0.327	0.341	0.343

Panel B: Alternative measure of suppliers' financial distress based on Ohlson's O-score

Dependent variable:		*Termination*			
	Pr. Sign	(1)	(2)	(3)	(4)
Conf Word Ratio × Supplier Fin Distress Alt	-	-1.258**	-1.160*	-1.311**	-1.212**
		(-2.10)	(-1.95)	(-2.22)	(-2.06)
Conf Word Ratio		-0.293	-0.312	-0.371	-0.391
		(-0.34)	(-0.37)	(-0.44)	(-0.47)
Supplier Fin Distress Alt	+	0.068**	0.063*	0.072**	0.068**
		(2.05)	(1.91)	(2.21)	(2.06)
Controls		No	Yes	No	Yes
Industry Pair × Year FE		Yes	Yes	Yes	Yes
Customer Firm FE		Yes	Yes	No	No
Supplier Firm FE		Yes	Yes	No	No
Firm Pair FE		No	No	Yes	Yes
S.E. clustered by industry		Yes	Yes	Yes	Yes
No. of observations		6,096	6,096	6,096	6,096
Adj. R-Squared		0.309	0.311	0.327	0.330